FINANCIAL STABILITY OF THE BANKING SECTOR

—INTERBANK CONTAGION, MARKET DISCIPLINE, AND MACROECONOMIC ROOTS OF CRISES

By

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ABSTRACT

This thesis conducts three different empirical studies and finds that some of the pre-2007 risk assessment model could underestimate the systemic risk of the banking sector and justifies an overhaul. First, it simulates the contagion impact of the UK interbank market. Subject to a number of assumptions (netting agreement, seniority, etc), it finds that the contagion is much severer if the simulation uses consolidated data than using unconsolidated data. Second, the thesis tests whether the riskiness of banks can be mitigated by peer interbank monitoring. Applying to UK market, the thesis finds little evidence of market discipline. The results are attributed to the lenders' assumption of "too-big-to-fail" and the shortness of loan maturity. Last, the thesis investigates whether banking sector difficulties are preceded by macroeconomic distress. In contrast to most existing studies, the thesis finds that economy still thrives in the "pre-crisis" in terms of increasing GDP growth and the recession is generally associated with the "post-crisis" period. The inconsistency of results is very likely due to imprecise crisis identification of earlier studies which identify crises too late on the basis of "event studies".

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CHAPTER ONE

INTRODUCTION

The importance of a stable and well-functioning banking sector has never been so manifest since the outbreak of the global credit crisis in 2008. Huge efforts have been made by the world's central banks to curb the adverse feedback loop between the banking system and the real economy. The aftershock of the banking crises is immense, not only because credit is extremely difficult to obtain, but in the sense that increasing pressure is exerted on taxpayers, employment and market sovereigns (following large-scale nationalization). It therefore becomes imperative for regulators and policy makers to assess the key risks facing the financial system and develop tools to detect systemic risk.

The thesis investigates empirically three different topics in managing systemic risk in the banking sector. First, it simulates the contagion effect of the UK interbank market. Second, it evaluates the interbank market discipline. Last, the thesis evaluates whether a systemic distresses is normally proceeded by macroeconomic downturns.

The first two topics are developed in Chapters Two and Three, which originate from two schools of thought on the implication of interbank linkages. On the one hand, Allen and Gale (2000) and Freixas, Parigi and Rochet (2000) regard the interbank exposure or the credit linkage between banks as a source of contagion. Default of any banks in the netting system is likely to trigger a chain reaction of defaults, resembling the fall of dominoes. The assessment of such an event is categorized by the IMF Global Financial Stability Report (2009) as the network approach to "track the reverberation of a credit event or liquidity squeeze throughout the banking system via direct linkage in the interbank market". On the other hand, Rochet and Tirole (1996) argue that, by generating incentives for lending banks to monitor borrowing banks, interbank exposures may also contribute to prudent market behaviour and reduce the risk of bank failures and systemic distress. This thesis tests these two theories empirically in the UK interbank market during the period before the current credit crisis. The results suggest wide-scale contagion impact in the worst scenario when a systemically important institution or group defaults. Moreover, the impact cannot be mitigated by peer monitoring incentives offered by the lending banks because the results indicate little evidence of market discipline in the UK interbank market.

The last topic on the macroeconomic indicators of systemic banking distress is evaluated in Chapter Four. Previous empirical studies argue that banking crises are most often caused by economic downturns as their results suggest that banking crises are often preceded by macroeconomic distress especially GDP falls (Gorton 1988, Kaminsky & Reinhart 1999, Demirgüç-Kunt & Detragiache 1998, and Hardy & Pazarbasioglu 1998). Therefore, macroeconomic figures can be used as early warning indicators to prevent crises. In contrast, the thesis finds that the pre-crisis period is associated with an economic boom, which then bursts sharply following crises. Hence, the results indicate that it is misleading to regard an economic slowdown as an indicator of systemic crises.

With the benefit of hindsight, section 1.1 explains the original contribution of the thesis from the perspective of the current global credit crisis. Section 1.2 summarizes some of the statistical facts about the UK interbank market, which will be studied in Chapters Two and Three.

1.1 Lessons from the Current Credit Crisis

The outbreak of the current credit crisis has once again shed light on the disadvantages of financial innovation. Sub-prime loans and mortgage-backed securities, once promoted as the solutions to low-cost access to credit, are now usually perceived to be the source of the problem. A wide range of banking or nonbanking financial institutions that have these assets on their balance sheets have come under strain during the crisis. To break the downward spiral between the financial sector and the real economy, trillions of pounds have been committed or spent by the world's economic leaders in the form of loans, asset purchases, guarantees, and direct spending.

However, while financial innovation "can misfire," it is possible that the benefits may more often outweigh the disadvantages. The root of the question, however, lies in whether, during the market upswings, banks have kept an eye on the downside effects and have provided enough capital buffers to reflect the risks accumulated through the cycle in order to absorb losses during the downswings. Unfortunately, sound risk-based decision making often gives way to short-termism. Such myopia builds up "excessive leverage" which eventually contributes to systemic banking crises such as the Asian or Nordic banking crisis in the 90s, the Latin American debt crisis in the 80s, and world-wide turmoil in the 1930s. The fact that the current banking crisis features the same problem was shown by the admission by former US Federal Reserve Chairman Alan Greenspan during October 2008 that the modern paradigm of risk assessment and management has essentially collapsed. It seems that the risk models that have been used either by investors or regulators are deeply misleading, both in terms of forecasting the future and implicitly guiding policy responses. They depended, perhaps unconsciously, too much on the assumption of market efficiency, i.e. that all investors behave rationally in assessing risk. Kurz (1997) showed that, when there is a wide consensus of investors who believe in market efficiency, the average riskless rate is high and the average risk premium is too low. In another word, the hypothetical low risk environment justifies a state where all investors choose an optimal level of leverage which is higher than when they have a normal degree of risk aversion; and financial regulators believe that no action needs to be taken for prudential reasons. In the end, the consensus jeopardized the entire global financial framework.

The investigation result of this thesis casts serious doubts on the pre-2007 risk assessment literature. In particular, it discovered that the existing literature has flaws in either assumptions or modelling, which could give false "safe" signals to regulators, although the contents and sample of this thesis were chosen before the outbreak of the current crisis.

In Chapter Two, the thesis examines the systemic implication of the interbank linkages in the UK. Previous studies simulated on European countries find only limited or low contagion impact. However, their results are crucially subject to various assumptions such as the evolution of market structures, the choice of data and default rate, as well as the number of banks who trigger defaults. In particular, the thesis compares the simulation using consolidated data to those using unconsolidated data in other studies. By using consolidated data, interbank exposures are selected from group consolidated balance sheets, rather than from subsidiaries' accounts. This means that, unlike the previous studies, the thesis assumes that the subsidiaries and their headquarters stand or fall together. The author's results show that the contagion impact is much severe if the simulation uses consolidated data than otherwise. Hence, data choices of this kind are very important for stress testing and a caveat is suggested to regulators in interpreting results from previous studies.

In Chapter Three, the thesis tests the interbank market discipline in the UK. It redefines the condition of interbank market efficiency and stresses it should satisfy in order: 1) risk sensitivity of interbank lenders; 2) effective risk control through interbank borrowing. Most existing studies only test the risk sensitivity without considering effective risk control. Others associate a reduction in bank risk with an increase in interbank borrowing, without first confirming if there is any monitoring incentive among investors. The results of either approach are subject to caveat to implicate that "market disciplines". Applying to UK market, the thesis finds little evidence to support the hypothesis of market discipline. This is explained by two elements: low risk sensitivity and the ineffectiveness of risk control. Investors in the UK market show little incentive to monitor their loans because most of the interbank borrowers are large institutions and are expected to be too-big-to-fail; the maturity of UK interbank loans is too short to allow for lender accountability. Moreover, as demonstrated in a theoretical model, the chapter shows that, even given incentives of peer monitoring, banks could choose a riskier investment portfolio to maximize their net expected return.

In Chapter Four, the thesis examines whether wide-scale banking distresses are preceded by deteriorating macroeconomic conditions such as a falling growth rate. As suggested in previous empirical studies, these indicators might serve as an early warning to regulators who can therefore choose responsive policies to prevent crises in advance. However, empirical studies in this thesis find that the economy still thrives in the "pre-crisis" period, although it deteriorates after the outbreak of the crisis. This inconsistency in results is very likely attributed to the imprecise identification of crises which identify crises too late on the basis of indirect symptoms. To accurately identify crises, this thesis uses stock market indices of banking industries as direct indicators of bank asset quality. The stock market data was largely unavailable for the underlying sample period in previous studies, so indirect indicators such as bail-outs, bank runs, mergers and acquisitions, and government liquidity injections are used. Moreover, the previous studies fail to address either the "pre-crisis bias" or the "post-crisis bias": the economic indicators or the explanatory variables during pre-crisis and post-crisis period may differ from those in tranquil times. Ignorance of this can lead to insignificance of variables. This thesis solves the bias by classifying a responsive variable into four categories and makes the estimation in the multinomial logit model.

1.2 The UK Interbank Market

The empirical studies conducted in the next two chapters are applied to the UK interbank market. Similar to other countries, the UK interbank market is a wholesale money market for the offering of deposits between commercial banks in a range of currencies. The market is based in London and is highly concentrated: over 70% of total lending between banks operating in the UK is accounted for by only 15 institutions, compared to 719 in the

U.S. (a comparison with other countries can be found in Table 2.1, Chapter 2). Wells (2004) points out that the structure of the interbank market is formed by "tiering". A small number of large banks transact with each other and a greater number of smaller institutions place excess funds with the larger banks.

Regarding the market instruments, the majority of the interbank transactions are in the form of loans, deposits and CDs, while less than 0.2% are in the form of commercial paper and bank bills. About 80% of the transactions are unsecured, accounting for around 27% of UK-resident banks' total assets. Foreign banks have a significant involvement in the UK interbank market due to London's position as an international financial centre. Only 36% of unsecured transactions are to a UK-resident bank. Furthermore, only around 2% to 3% of the total interbank assets or liabilities recorded in balance sheets have a duration of over five years, while more than 80% are for less than three months, of which around a quarter are on demand.

Limited data is available on the UK interbank market. Individual bilateral time series' on actual interbank rates and quantities are not released to public. Even at the supervisory and regulatory levels, the Financial Service Authority (FSA) only obtains the large exposures, i.e. the size and counterparty for each bank's 20 largest exposures and any other exposures exceeding 10% of its Tier 1 capital. However, many banks, mostly large in size, do release their balance sheets showing the quantity of the aggregate lending and borrowing in the interbank market annually or in 6 month time. The data limitation problem at bilateral level leads the author to use entropy maximization method as to be specified in next Chapter.

CHAPTER TWO

ASSESSING INTERBANK CONTAGION RISK USING CONSOLIDATED DATA

2.1 Introduction

The benefit of the interbank market gives an optimal allocation of resources. Funds are distributed efficiently from banks that have a comparative advantage in terms of deposit collecting, but are less skilled in investing capital, to banks that are experts in growing assets, but suffer from a lack of funding. However, while such credit linkage between banks provides a risk sharing mechanism, it is also an important source of contagion. Since the late 1990s, the contagion risk in the interbank market has been assessed by researchers at many central banks. Many of them resort to a conditional simulation that starts by assuming that a bank, or a group of banks, is not able to repay their borrowings. Contagious defaults occur if the losses on the exposure to the defaulting bank exceed the capital of a creditor; the losses at the creditor banks are then computed. As each default weakens the surviving banks, it may end up causing a chain reaction of defaults, resembling the fall of domino pieces. The existing empirical studies indicate that the scope of contagion varies dramatically across countries. For countries such as Germany and Denmark, the contagious assets, as a percentage of the total assets, amount to 88% and 72% respectively, while the scope is quite limited in Switzerland and Austria whereby the affected assets never exceed 1% of the total industry assets.

However, as the simulation is "conditional" owing to a number of assumptions regarding various issues including research focuses and data restrictions, etc., the results are subject to important caveats and biases. For example, as the interbank data are aggregated and do not contain specific information on the counterparty that a bank lends to or borrows from, the complete interbank positions, where each bank symmetrically holds claims on all other banks in the systems, have to be estimated. The incompleteness in data also prevents most authors from including the entire lines of interbank business. Besides, studies are inconsistent in choosing sample dates and defining contagion mechanisms, as well as assuming the loss given default. All these factors could result in bias in either direction and, as a result, the interpretations of the simulation results are not directly comparable across countries.

Among the various sources of bias, the issue of estimating consolidated exposure using unconsolidated data is mostly ignored by researchers. Great divergence may arise between the two types of data. Consolidated financial statements present financial information about a parent's undertakings and its subsidiary undertakings as a single economic unit, while unconsolidated statements present them as separate units. As the banking industry becomes increasingly integrated and concentrated, large banks usually own a significant number of subsidiaries, which are most likely to stand or fall together. Using unconsolidated data in the contagion simulation could seriously affect the robustness of results.

The chapter analyzes this issue by simulating the contagion effect in the 2004 UK interbank market comprising 16 UK-owned banks and five foreign groups, using consolidated data. To facilitate the simulation, it is crucial to have the data of the bilateral interbank exposure, i.e. the amount of interbank lending and borrowing to a specific bank. However, this type of data is difficult to obtain even at the supervisory level for many central banks. Banks only release aggregate data revealing total interbank exposure. Following existing studies, the author uses Entropy Maximization method (ME) to estimate the bilateral interbank exposure. The method assumes that banks seek to maximize the dispersion of their interbank activity, which means each bank symmetrically holds claims on all other banks in the system. This is sensible in that the amount that a bank *I* lends to a bank *J* depends on the share of the bank *I*'s total lending to the market and the share of the bank *J*'s total borrowing from the market. However, it resembles a complete market structure proposed by Allen and Gale (2000) where every bank is symmetrically linked with all others. This assumption rules out relationship banking in which banks normally have a few fixed clients to transact with. Moreover, it could underestimate the contagion effect of the UK interbank market which is more close to the money centre market structure proposed by Freixas, Parigi and Rochet (2000) where all other banks transact only with the money centre bank.

The author deals with the drawbacks of ME by manually changing the weights of interbank exposure between banks. This is realized by increasing the exposure of intra-group, increasing the exposure with money centre banks, or increasing the exposure of transactions with foreign banks. The simulation results suggest that there is a huge knock-on impact using consolidated exposure: 89.48% of the total balance sheet assets are affected in the worst scenario at a rate of 100% loss. The scale of contagion prevails disregarding the type of market structure, although the contagion propagates faster under a money centre market structure than under the complete market structure. Nevertheless, contagion impact varies substantially at different loss rates. If the loss rates are lower than 40%, no contagion will occur. The results also show that the market is less contagious when lending and borrowing is mostly solved within the same banking group; and increasing interbank transactions to foreign banks rather than local banks could effectively decrease the severity of contagion due to risk diversification.

However, in contrast to existing studies on UK, the severity of contagion is much higher. For example, in the same benchmark model, the contagion impact of this chapter is four times higher than that of Wells (2004) in which only 25.25% assets are affected. The inconsistency is largely due to the consolidated data used in this chapter. Illustrating in a pseudo-four-bank system using both consolidated and unconsolidated exposure, the author shows that the banking system of consolidated exposure which is more likely to experience contagion than the system of unconsolidated exposure, if the possibility is measured by the average interbank exposure relative to tier-I capital is larger in the system of consolidated exposure than that of unconsolidated exposure. Moreover, if the contagion impact is measured by the percentage of total banking sector assets, the author demonstrates that simulation using consolidated exposure is more contagious when the average capital position is between the consolidated interbank exposure and the unconsolidated exposure.

Furthermore, the author assess years before 2004 to see if the scope of contagion has changed over time. As most small and mid-sized banks do not release their annual reports prior to 2002, only two years are assessed prior to 2004. The investigation suggests a similar wide-scale contagion between 2004 and 2003, accounting for 90% of total banking sector assets, but a limited impact in 2002, accounting for only 12.57%. This is attributed to higher interbank exposure relative to Tier-1 capital in 2003 and 2004 compared to 2002. However, as far as cases of contagion are concerned, 2002 seems to be the year most likely to trigger a contagion with highest number of initial defaults leading to contagion. Analyses show that the standard deviation of the ratio of interbank exposure to Tier-1 capital across banks is highest in 2002 and lowest in 2004. This implies systemically, the interbank exposure is more concentrated in a few banks in 2002 than other two years.

The rest of the chapter is organised as follows: section 2.2 explains sources of contagion and reviews theories on the relationship between market structure and contagion effects; section 2.3 looks at the existing studies of contagion simulation owing to interbank exposure, various assumptions and their biases against the robustness of simulation results; section 2.4 simulates the systemic risk of the UK interbank market in 2004 using consolidated data and section 2.5 concludes.

2.2 Literature Review

Under normal conditions, interbank markets provide benefits in the form of optimal allocation of resources. Funds are distributed efficiently from banks that have a comparative advantage in collecting deposits, but are less skilled in investing them, to banks who are experts in making investments, but lack funding. Interbank transactions that achieve this function include intraday debits on payment systems, overnight and term interbank lending in the money markets, securities, FX settlements and off-balance-sheet instruments such as over-the-counter (OTC) derivatives.

Lending banks prefer liquid assets of interbank loans to cash reserves, as they could reduce the opportunity costs of holding the latter. However, the interbank market does not always function properly, especially during crises, when all banks find it optimal to withdraw bank loans for fear that other banks will not be able to honour their obligations if their depositors withdraw all their wealth (Freixas, Parigi and Rochet 2000). It is therefore questionable for prudential purposes to rely solely on interbank loans as a better liquidity cushion than cash resources. As Rochet and Tirole (1996) put it, interbank transactions reduce the transparency of a bank's balance and off-balance sheet data and complicate the assessment of a bank's actual liquidity ratio.

However, it is more worrying that the netting obligations of the interbank market pose a potential risk of contagion from the failure of one institution to another. The propagation, often referred to as "systemic risk", is a serious concern for all sectors of the economy. Anxiety over systemic risk in the banking sector is perhaps the strongest concern for regulators because of its close connections with the other industries that form a broader economy. Moreover, the risk does not diminish due to the fact that interbank loans or transactions, neither collateralized nor insured against, now make up an increasingly large proportion of banks' balance sheets in many countries (Lublóy 2005).

The following sections examine several sources that trigger the interbank propagation and explore the causality relationship between interbank market structure and the severity of contagion.

2.2.1 Sources of Contagion

Interbank markets are susceptible to contagion failure from three major sources: macroeconomic impulses, information externalities and explicit credit linkages. Macroeconomic impulses refer to exposure of the market to a common shock or the sudden movement of aggregate risk factors such as interest rates, exchange rates, equity index rates, etc. In that case, contagion risk is imposed on all banks simultaneously and the movement of these risk factors is often related to business cycles and triggered by domestic and external macroeconomic imbalances. As a separate source, macroeconomic impulses do not stress the credit linkage between banks in the interbank market and is not the focus of this chapter. However, the author will discuss the macroeconomic shock on the entire banking sector in Chapter Four.

The second source is information externalities which originally refer to a self-fulfilling bank run by depositors (Diamond and Dybvig 1983). In the interbank market, banks are depositors themselves in terms of credit lending. When there is an aggregate shortage of liquidity (aggregate withdrawal demand in the market is greater than the total stock of the short-term asset), individual banks find it optimal to withdraw all their deposits for fear that the other banks will not be able to honour their netting obligations if their depositors have withdrawn all their wealth and if a sufficiently large fraction of deposits in other banks is withdrawn (Freixas, Parigi and Rochet 2000). A "gridlock" or "coordination failure" occurs in which interbank markets cease to function as they should under normal circumstances. Moreover, Allen and Gale (2000) show that coordination failure will cause the originally solvent, but illiquid, bank to become insolvent and, in turn, the healthy banks on the nodes of the netting system will also find themselves on the edge of failure. The UK small bank crisis in the early 1990s gives a good illustration of a "gridlock" status.

The chapter focuses on the contagion that comes from the explicit credit linkages of the interbank market. It differs from the information externalities in that the contagion is not a self-fulfilment rational or irrational behaviour. Instead, it occurs with a chain reaction, where the propagation spread through a chain of interbank loan default. The initial default is an idiosyncratic bank failure regardless if it is caused by either macroeconomic distresses or microeconomic deficiencies.

2.2.2 Impact of Market Structure

The risk of interbank contagion is sensitive to the pattern of linkages and the size of the exposures on the node of the netting system. Allen and Gale (2000) consider two types of market structure and compare their systemic stability. One is a complete market structure (Figure 2.1), where every bank is symmetrically linked with all the others; the other is an incomplete market structure (Figures 2.2 and 2.3) where banks have connections only to a few neighbouring counterparts. They contend that the former is more stable and may involve no contagion at all, while the latter is inclined to be more fragile. This is because, for a given total interbank exposure, if the market is complete, each bank holds a lower amount of interbank assets than in the case of the incomplete market, thus lowering the risk that a bank default may spread to other banks (Mistrulli 2005). To consider it in another way, the contagion effect is dampened or diversified, since the symmetrical holding of deposits of the same value within banks can be simply cancelled out. Figure 2.2 and Figure 2.3 both exemplify incomplete markets, but differ in interconnectedness, another evaluation of the extent of contagion put forward by Mistrulli (2005). Contagion risk is lower in Figure 2.3 when the market is segregated and any contagion is therefore limited to banks that link together.

Figure 2.1: "Complete market structure" according to Allen and Gale (2000)

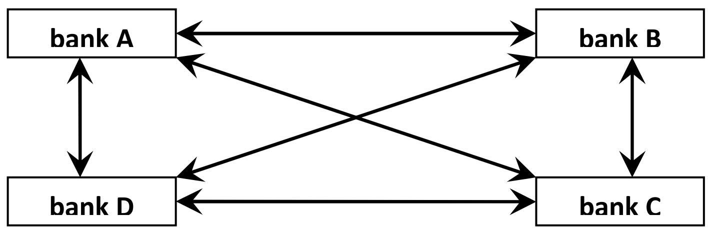


Figure 2.2: "Incomplete and interconnected market structure" according to Allen and Gale (2000) and Mistrulli (2005)

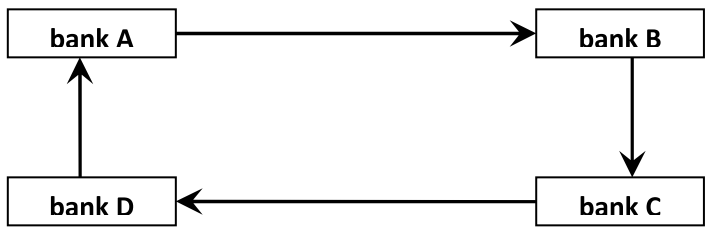
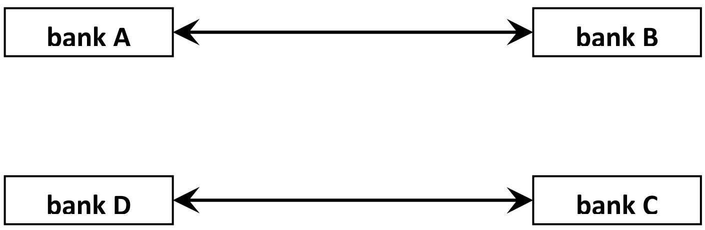
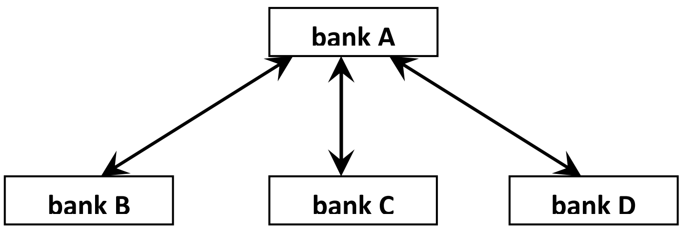


Figure 2.3: "Incomplete and disconnected market structure" according to Allen and Gale (2000) and Mistrulli (2005)



Modelling a money centre market structure, Freixas, Parigi and Rochet (2000) argue that the contagion impact might be dramatically different even under the same structure, as it is subject to the hierarchical position of the initial bank that fails. A money centre market is a centralized banking system (see Figure 2.4) where all other banks transact only with the money centre bank which thus has the highest exposure to the entire system. Compared to contagion impact initialized by the distress of any other bank, breakdown of the money centre bank could result in paralysis of the whole system.

Figure 2.4: "Money Centre Model" according to Freixas, Parigi and Rochet (2000)



Interbank markets in many countries (Germany, Belgium, Hungary, to name a few) are featured as multiple money centre market structures, and some of them have changed from a complete market structure. The prevalence reflects a common trend of financial consolidation/integration and internationalization as far as the cross border interbank market is concerned. One explanation for this trend by Mistrulli (2005) is that banks could exploit the economy of scale by pooling the liquidity together. He argues that the consolidation trend has a mixed impact on systemic risk, subject to the interconnectedness of the system. He illustrates his statement with two concentrated systems (see Figures 2.5 and 2.6), one showing the two money centres as connected, and the other where they are disconnected.

Figure 2.5: "Interconnected money centre bank market structure" according to Freixas, Parigi and Rochet (2000) and Mistrulli (2005)

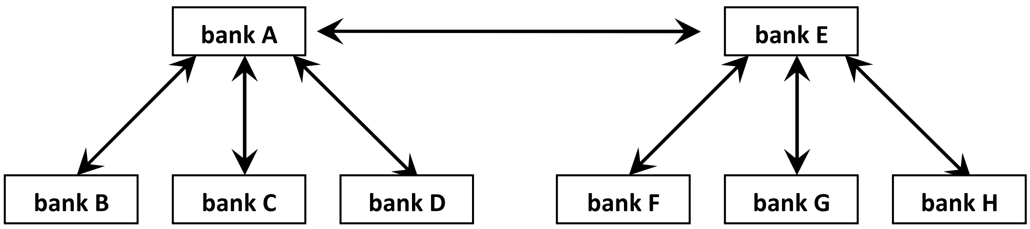
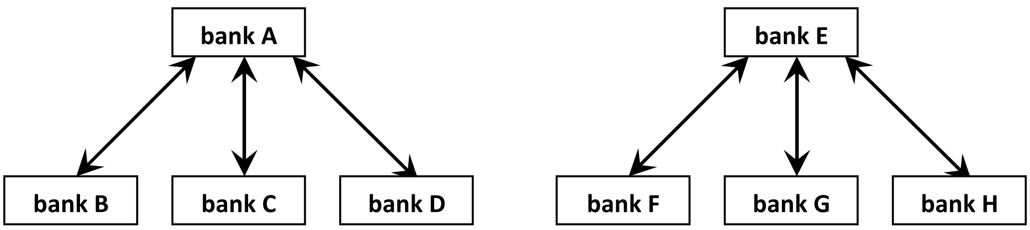


Figure 2.6: "Disconnected money centre bank market structure" according to Freixas, Parigi and Rochet (2000) and Mistrulli (2005)



He concludes that the risk of systemic paralysis is lower in Figure 2.6 than in Figure 2.5 in the worst case scenario where the initial failure is triggered by a money centre. This is because, when the two money banks are connected in Figure 2.5, the degree of incompleteness increases comparable to Figure 2.2. Similarly, Figure 2.6 is comparable to Figure 2.3 in connectedness and incompleteness. Therefore, it is inferred that the overall contagion effect of financial consolidation is not a priori determined.

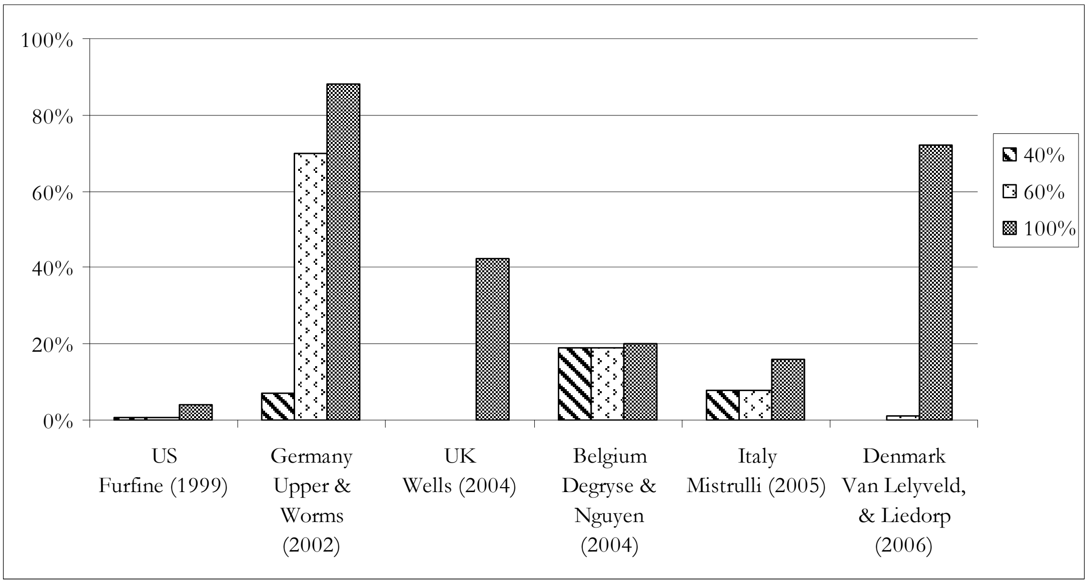
2.3 Simulation of Contagion Risk: Robustness of Existing Empirical Studies

A number of comparable studies (see Table 2.1) contain simulations to assess the contagion risk of the interbank market in different countries. The simulation starts by assuming a bank, or a cluster of banks, is unable to repay their obligations in the interbank market. The losses of the creditor banks are calculated. Contagious defaults generally arise when the losses as a result of the exposures to the defaulting banks exceed the capital of a creditor bank. As each default weakens the surviving banks, it may end up causing a chain reaction of defaults, resembling the fall of domino pieces. Section 2.3.1 analyses the simulation results of authors in different countries. However, due to different research focus and data restrictions, the simulation is performed based on a number of assumptions/conditions which may either bias the magnitude of contagion or cause the contagion impact to be incomparable across studies. Section 2.3.2 explores various sources of bias and assesses their influence on the results.

2.3.1 Contagion Impact across Countries

On the whole, the existing studies imply that contagious defaults are quite unlikely in the sense that they occur in very few cases; nevertheless, if they do occur, they might have a considerable impact on the health of the banking sectors of many countries. Figure 2.7 illustrates the contagion impact simulated in these papers spread across countries. Comparable results are available at 40%, 60% and 100% loss given default rate (LGD).

Figure 2.7: Contagion across countries (in % total assets of banking system)



Note: 40%, 60% and 100% represent loss given default rate (LGD).

In the U.S., for example, Furfine (1999) finds that the failure of the top two most significant banks causes, at most (LGD=100%), the failure of banks holding 4% of the assets in the banking sector. If loss rates are kept to less than 60%, asset loss would never be expected to exceed 1% of total assets. In contrast, investigating the German market, Upper and Worms (2002) discover that contagious defaults as a percentage of total banking assets could sour to 88% if no loss can be recovered immediately. Even at 60% LGD, the contagion still affects around 70% of total industry assets. However, they suggest that the result is exaggerated without considering any banking supervision, regulation and a safety net. Under a perfect safety net, the maximum effect at 100% LGD drops to under 15% of total assets.

Regarding the UK interbank market, Well (2004) finds that a multiple bank failure could affect 42% of total assets under a money centre structure. However, he implies that this scenario is rare and is most likely triggered by the assumed insolvency of a large UK-owned bank. Since large UK-owned banks generally have a high credit profile, their default probability is generally low, thus indicating a low possibility of a knock-on systemic failure. Nevertheless, Well (2004) concludes that, in many cases, the contagion could result in banks holding over 50% of total industry assets suffering losses exceeding 10% of their Tier-1 capital[1]. Similar to the UK, Van Lelyveld, & Liedorp (2006) find that the bankruptcy of one Dutch bank could have a considerable impact on other banks, causing a contagious effect on 72% of total banking assets. However, if the loss rate is assumed to be less than 60%, asset loss is dramatically decreased to less than 1%. For Belgium and Italy, the contagion impact is relatively lower, accounting for less than 20% of total assets.

In many countries, except for Belgium and Italy in Figure 2.7, the severity of contagion varies substantially for different loss given default rates (LGD). As LGD can be interpreted as an immediate loss rate following default, it suggests that if there is an efficient crisis resolution mechanism or lender of last resort, the contagion can effectively be kept at a low level.

Moreover, three countries listed in Table 2.1 are not plotted in Figure 2.7, because the contagion impact in those countries is comparable only at 100% LGD. They are: Switzerland (Sheldon & Maurer 1998), Hungary (Lubloy 2004) and Austria (Elsinger, Lehar

[1] Tier 1 capital is the core measure of a bank's financial strength from a regulator's point of view. It consists primarily of shareholders' equity but may also include preferred stock that is irredeemable and non-cumulative and retained earnings.

& Summer 2002). For LGD at 100%, these authors find that the extent of contagion is quite limited; close to zero in Hungary and Switzerland and Austria's affected assets never exceed 1% of the total banking sector assets.

2.3.2 Assumptions & Biases

Interpretation of the severity of contagion in various studies above is subject to important caveats. Data limitations at different levels and distinctive assumptions not only make the contagion impact incomparable across countries, but subject their results to bias in the first place. This section explores the sources of bias and analyses how these aspects could cause an overestimation or underestimation of the contagion risk in a country's interbank market. As this chapter also makes similar assumptions, the empirical result may also subject to similar bias at different scale.

2.3.2.1 Aggregated vs. Bilateral Data

As can be seen in the first column of Table 2.1, except for the US, all interbank transaction data are authoritative. On a confidential basis, central banks in different countries, as prudential supervisors, regularly receive balance sheet data. However, it is difficult for some countries such as Switzerland and the UK to determine the precise structure and interlinkages of the interbank market, because those reports do not disclose the bilateral interbank positions of each bank. In Switzerland, such information is aggregated or one-to-all reported, i.e. the total size of a bank's interbank lending or borrowing in the market is disclosed to the regulator, but the counterparty to which it lends to or borrows from is unknown. In the UK, however, partly aggregated or one-to-some information is available, since banks are required to report the several largest credit exposures to some specific counterparts. In an effort to perform a simulation on contagion risk, it is inevitable that one-to-one interbank exposures must be estimated. The entropy maximisation (ME) approach, first used by Sheldon and Maurer (1998), is commonly adopted by others that suffer a similar problem. However, when estimating bilateral interbank positions, the ME approach assumes that banks seek to maximize the dispersion of their interbank activity. This setup could alter the original market structure, often a concentrated money centre structure (see the 5th column of Table 1), towards a complete structure described in Allen and Gale (2000). As Degryse and Nguyen (2004) argue, it cannot be determined a priori which is more contagious: a complete market structure or a money centre structure. The result depends on the robustness of money centre banks, as the direction of bias of using an ME approach is unknown. However, authors who perform simulations on both bilateral exposures and aggregated data using ME find that the severity of contagion is similar for different datasets.

Data incompleteness problems also exist in cross border exposure, as data on overseas banks are usually only available as an aggregate position according to different geographical regions; each region is thus treated as a counterpart with which banks are transacting. This arrangement in Van Lelyveld, & Liedorp (2006), Wells (2004), and Degryse & Nguyen (2004) could overestimate the contagion risk because it is very rare that a region could default as a whole. However, Van Lelyveld, & Liedorp (2006) argue that such a scenario should not be overlooked if taking account of the examples of the Asian crisis in 1997 and the event of September 11, 2001. Moreover, a large share of total interbank lending in many countries is by resident-bank to non-resident banks. To obtain a comprehensive understanding of the scope for contagion within the UK banking system, implied by Wells (2004), bilateral exposures would have to be estimated for all banks within the global system, including transactions between overseas banks. Unfortunately, as data are not readily available for banks that are beyond the supervision of central banks, simulation is restricted to domestic-resident banks, i.e. domestic-owned banks and branches or subsidiaries of foreign banks located within the country in the study. This amounts to spreading large cross-border exposures into the domestic market, creating serious bias to the simulation results.

2.3.2.2 Consolidated vs. Unconsolidated Exposure

Nearly all studies estimate consolidated exposures between banking groups using unconsolidated data, selected from the balance sheets of subsidiaries of individual banking groups. This could seriously bias the simulated contagion of a country, especially where it has a highly concentrated banking system (many are money centre structured) and the large banking groups usually own a significant number of subsidiaries. Well (2004) also considers the importance of consolidated exposure between banking groups, since the entities/subsidiaries of a large group are likely to stand or fall together. Unfortunately, no studies discuss the influences and direction of this bias on the contagion risk. This chapter explores this issue later by simulating a pseudo-four-bank system. The results suggest that, as far as average interbank exposure relative to capital is concerned, the simulation using

Table 2.1: Comparison of the recent literature using matrix analysis

Country Author(s)	Interbank data	Completeness of information	ME method	Market structure	Domestic/ foreign & No. institutions	Interbank credit exposure included	Collateralized/ uncollateralized	Sample date/period	Fixed/ endogenous loss ratio θ
US Furfine (1999)	Public available	Bilateral (one-to-one)	No	Unspecified	719 Domestic	Deposits	Uncollateralized	Daily Feb.-Mar. 1998	A range of fixed
Switzerland Sheldon & Maurer (1998)	Authoritative	Aggregated (one-to-all)	Yes	Unspecified	576 Domestic	Deposits	Both	1987-1985	One fixed
Germany Upper & Worms (2002)	Authoritative	Partly Aggregated (one-to-some)	Yes	Money centre	3246 including foreign branches	Deposits	Both	Dec. 1998	A range of fixed
Sweden Blavarg and Nimander (2002)	Authoritative	Bilateral	No	Money centre	108 including foreign branches	FX settlement, Deposits, Securities, Derivatives	Uncollateralised	Sep. 1999-Sep. 2001	A range of fixed
Austria Elsinger, Lehar & Summer (2002)	Authoritative	Partly Aggregated	Yes	Money centre	881 Domestic	Unspecified	Unspecified	Sep 2002	Endogenous
Denmark Van Lelyveld, & Liedorp (2006)	Authoritative	Partly Aggregated	Yes	Incomplete less connected	88+5 Foreign groups	Deposits	Uncollateralized	Dec. 2002	A range of fixed
UK Wells (2004)	Authoritative	Partly Aggregated	Yes	Money centre	27+5 Foreign groups	Deposits	Uncollateralized	31 Dec. 2000	A range of fixed
Belgium Degryse & Nguyen (2004)	Authoritative	Partly Aggregated	Yes	Form complete market to money centre	65+2 Foreign groups	Deposits	Both	Dec. 1992-Dec. 2002	Partly Endogenous
Hungary Lubloy (2004)	Authoritative	Bilateral	No	Moderately concentrated	39 Domestic	Deposits	Uncollateralized	150 days in 2003	One fixed
Italy Mistrulli (2005)	Authoritative	Bilateral & Aggregated	Yes	Gradually converge to money centre structure	Domestic (No. Unknown)	Deposits, Repo	Both	1990-2003	Fixed θ

consolidated reporting is more contagious than that using unconsolidated reporting. However, if the contagion is measured by assets affected in terms of a percentage of total industry assets, it is not evident, depending on the capital adequacy of existing banks following the initial default.

2.3.2.3 Scope of Interbank Transactions

It can be seen from Table 2.1 that most authors include only interbank loans/deposits as interbank credit exposure. This is because other interbank transactions, including securities, repos, FX settlements and off-balance-sheet instruments such as over-the-counter (OTC) derivatives, are either not included in the balance sheet reporting (e.g. Denmark) or not reported by the type of counterparty (e.g. U.S.). Exclusion of these exposures may underestimate the contagion risk of a particular country. However, authors like Wells (2004) and Furfine (1999) defend that excluded items such as repos and OTC derivatives are either collateralized or small in size relative to on-balance items. Moreover, Wells (2004) suggests that not all the excluded exposures are to other banks and the absence of information on other types of exposure is mitigated by various collateral netting agreements.

2.3.2.4 Sample Dates and Period

Table 2.1 also lists the sample date/period that is investigated in the respective studies. Not all papers take an evolutionary view of the interbank market. Studies such as those examining Germany, Austria and Denmark assess the contagion risk based on a fixed-date balance sheet report. It is not clear, therefore, whether the contagion impact has been changing over the previous period. Besides, Van Lelyveld and Liedorp (2006) imply that studies that are based on the December report are subject to the end-of-year effect. This means that reported exposures at this date are lower compared with the rest of the year.

2.3.2.5 Contagion Sources and Definitions

Nearly all studies assume the contagion is triggered by the failure of a single bank in the system due to some exogenous shock, and that the distribution of idiosyncratic shocks, which trigger contagion, is uniform among banks and does not change over time. It is a relatively strong assumption, since completely idiosyncratic shocks are rare. As explained in section 2.1.1 on sources of contagion, if the interbank market is exposed to common shock driven by macroeconomic impulses, it is more likely that several banks will be simultaneously affected and its influence on the whole system is obviously greater than individual bank failure. Elsinger, Lehar and Summer (2002) is the only study that considers macroeconomic impulses. However, idiosyncratic failures did occur in many countries, e.g. the Barings Bank collapse of 1995, and potential contagion feared by the market still warrants the regulators to act as lenders of last resort. Latest examples include the British bank Northern Rock, for which the Bank of England arranged an emergency loan facility in 2007 to support its short-term liquidity problems, allegedly as a result of over-exposure to the failing US sub-prime mortgage market. Similarly, a government sponsored bail-out in 2008 was arranged for the investment bank Bear Stearns due to a panic run on its short-maturity bonds (Asset Backed Commercial Paper) by which the bank is heavily financed.

Furthermore, the assumption of idiosyncratic shocks has a policy implication that it could help to identify which banks are crucial to the stability of the entire system.

Apart from the sources of contagion, the existing studies vary in their definition of contagion, or the condition of contagious default. As mentioned previously, most studies regard the occurrence of contagion as when the actual/immediate loss of a bank's interbank credit exceeds the bank's Tier-1 capital. Blavarg and Nimander (2002) apply the definition that the Tier 1 capital (capital ratio) of the bank falling below the required level of 4% is assumed to constitute a default. Therefore, the latter definition is more prudent in assessing contagion risk, as the contagious default occurs more easily. Elsinger, Lehar and Summer (2002), however, define contagious insolvency as being the case when income received from other banks, plus the income position of non-interbank activities, minus the bank's own interbank liabilities, becomes negative. However, since they defer from other studies in the source of contagion, it is not possible to appraise whether their definition of contagion is more prudent. Moreover, the bias caused by different definitions cannot be judged until a benchmark definition is agreed to be applicable to all the banks in a country.

2.3.2.6 Loss Given Default Rate (LGD)

A. Choice of LGD

Some authors in Table 2.1 assess contagion at only 100% LGD while many others apply a range of LGD. The former assumes the largest immediate loss rate mainly because the magnitude of contagion in Switzerland and Hungary is very limited and a stress test gives a prudent picture of the worst possible scenario. However, this assumption ignores mitigation factors such as a safety net (Sheldon & Maurer 1998), market expectations (Lubloy 2004), and banks' reaction to shocks (Mistrulli 2005). In reality, argued by these authors, both banks and regulators could respond to the shock by providing various crisis warning or crisis management schemes.

Other factors such as netting agreements and seniority relative to other claims can also affect immediate loss and, in turn, affect the simulation result. In a netting agreement, default interbank loans are netted off from the interbank liability of the same counterpart, thus decreasing the actual incurred loss. In the event of bankruptcy, if interbank loans are senior to other claims, the immediate loss could be less than otherwise, i.e. subordinate in claim order. The impact of these two factors, as well as the efficiency of response, could be reflected in the simulation by applying a range of LGD rates.

Last but not least, the choice of LGD rates changes over time. For example, Mistrulli (2005) suggests that financial consolidation, by leading to the creation of larger and more diversified banks, may lower the probability of banks defaulting.

B. Fixed vs. Endogenised LGD

Although a range of fixed LGD reflects the common mitigation factors of banks, as explained in the previous section, Mistrulli (2005) notes that it has the drawback of assuming that each bank faces similar constraints when raising capital, which is in contrast with theories on bank-lending channels. However, he also points out that it is difficult to introduce banks' heterogeneity into the contagion mechanism since banks' failures are rarely observed empirically. For that reason, most studies select common LGD rates for all banks, according to historical cases of bank failure and existing literature. For example, based on previous studies, Furfine (1999) focuses on two LGD, 40% and 5%. According to James (1991), in the middle of the 1980s in the U.S. the average value LGD was 30% of the book value of the banks' assets, and an additional 10% covered the administrative costs. Kaufman (1994) estimates a 5% LGD based on the failure of Continental Illinois. Upper and Worms (2002) refer to an article in the Financial Times which mentions that the preliminary LGD when the BCCI went bankrupt in 1991 was assumed by creditors to be 90%.

Nevertheless, there are two studies that endogenize the loss rates. Degryse & Nguyen (2004) depend upon the LGD of all the other banks to which a given bank is linked in order to construct its LGD. However, the endogenization is partly possible because it assumes an exogenous LGD on assets other than interbank loans and it assigns a fixed 60% LGD on the first domino. More interestingly, the simulation results suggest that the magnitude of contagion is broadly similar to the results of simulations that assume a fixed LGD for all assets. In another article, Elsinger, Lehar & Summer (2002), fully endogenize the LGD rate. However, as their assumptions of contagion source and contagion mechanism are generally different from other papers, it is not approriate to interchange their method with others and assess the difference when the LGD is endogenized.

2.4 Simulation Using Consolidated Data of UK Banks

2.4.1 Definitions and Assumptions

The simulation begins by assuming that a bank, or a cluster of banks, fails due to some exogenous shock and is unable to pay its interbank obligations. The losses are then calculated at the creditor banks from whom the first-default bank has borrowed. A fixed LGD rate is set a priori to measure the actual loss. Contagion occurs if the actual loss exceeds the Tier-1 capital of a creditor. Although the contagion mechanism presented below allows any number of banks to trigger contagion, the simulation begins with an individual bank in order to compare with existing studies that let each bank fail sequentially (regarded as one scenario). Formally, the contagion condition is expressed as

$$x_{ij}\theta \geq c_i \qquad (2.1)$$

where θ is the pre-set loss rate, χ_{ij} denotes a creditor bank I's interbank lending exposure to a borrowing bank J, and c_i is bank I's Tier-1 capital. Tier-1 capital is defined as shareholders' equity.

For each scenario, if no banks default following the initial failure (i.e. the contagion condition is not satisfied), it is deemed that there is no contagion risk for the chosen trigger bank. However, if at least one bank is insolvent as a result of the loss realized on its interbank claim, the scenario experiences the first round of contagion. The first round may involve more than one bank. In that case, a second round of contagion will occur if the combined actual losses on the exposure to the defaulting banks exceed the Tier-1 capital of existing banks. The process is iterative in calculating the credit losses and comparing them with the capital. Therefore, a general form of the contagion condition can be used to take account of N number of defaulting banks:

$$\sum_{j}^{N} x_{ij} \varphi_j \theta \geq c_i \tag{2.2}$$

where φ_j is a dummy variable that equals 0 if bank *j* has survived and 1 if it goes bankrupt and other parameters are interpreted consistent with condition (2.1).

Based on Literature Review and existing empirical studies in section 2.2 and section 2.3.2 above, the simulation of this study makes a number of other assumptions as follows:

(i) Contagion is triggered by an exogenous idiosyncratic shock and no other sources of contagion exist;

(ii) The distribution of idiosyncratic shocks, which trigger contagion, is uniform among banks and does not change over time;

(iii) Entities/subsidiaries of a large group stand or go bankrupt together;

(iv) Contagious default occurs when the actual/immediate loss of a bank's interbank credit exceeds the bank's Tier-1 capital;

(v) No netting agreements apply when calculating the loss on the exposure to the default bank;

(vi) Interbank loans are senior to other claims on the capital of the default bank;

(vii) LGD rates less than 100% are able to reflect the mitigation factors of a safety net, market expectation and banks' reaction to shocks at different levels.

(viii) There is no heterogeneity for individual banks in the contagion mechanism.

2.4.2 Data Description

Interbank loan/deposit data are chosen from the annual reports of 16 major UK-owned banks which release consolidated balance sheets. According to asset size, banks are categorized into large, mid-sized, and small banks. Therefore, the sample contains six large banks, whose assets are over £100 billion; six mid-sized banks, whose assets are between £10 billion and £100 billion, and four small banks, whose assets are below £10 billion.

As the UK banking system is highly concentrated, the 16 banks cover around 71% of the total interbank loans of UK-owned banks in 2004, calculated from the data published by Bank of England. The rest of the domestic banks are all small banks and are not included in the sample because almost all of them do not release their balance sheets to the public. Moreover, the individual failure of these small banks is not considered to be likely to have a sizable impact in terms of contagion[2]. In addition, for branches or subsidiaries of foreign-owned banks located within the United Kingdom, the Bank of England provides aggregated data of the outstanding interbank deposits/loans. The information available is divided into five regions, i.e. other EU, America, Japan, Other developed and Other countries (the rest of the world). The size and share of each region in terms of total interbank loans and deposits are given in Table 2.4.

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[2] The joint default of small banks may cause contagion. However, as the total interbank assets of the small banks exceed the combined interbank assets of many largest banks, the joint default amounts to assuming a common macroeconomic shock to all banks. Hence, instead of including the aggregate data of small banks, the chapter simulates the common shock later by assuming that most of the interbank assets of a bank turn out to be defective. The last section will examine this scenario from 2002 to 2004.

Table 2.2: UK interbank loans and deposits in December, 2004

Bank Group	Interbank Assets		Interbank Liabilities	
	Billion GBP	% of Total	Billion GBP	% of Total
UK-owned banks	327.139	66.52%	333.961	67.80%
Other EU	58.373	11.87%	68.436	13.89%
American	33.457	6.80%	24.928	5.06%
Japanese	8.359	1.70%	6.344	1.29%
Other developed	55.588	11.30%	58.926	11.96%
Other	8.896	1.81%	2.333	0.47%
Total	491.818	100%	492.561	100%

Source: Bank of England.

The interbank information in the balance sheets from both the individual banks and the central banks are aggregated in nature. In order to run the simulation, the bilateral position x_{ij} needs to be estimated. Given the 16 UK-owned banks and an aggregate position for foreign banks of five regions, this can estimate a 21 by 21 matrix of interbank exposures of money market loans and deposits.

2.4.3 Estimating Bilateral Lending Exposure— Entropy Maximization

To identify the contagion process in section 4.1, the bilateral exposure x_{ijs} should be estimated in equation (2.2), based on the aggregated information of interbank assets and liabilities. The method used is entropy maximization, first applied by Sheldon and Maurer (1998), who have the similar data limitations. The ME approach can be illustrated by the following $N \times N$ matrix denoting the interbank position between N banks:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{iN} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{Nj} & \cdots & x_{NN} \end{bmatrix}$$

x_{ij} represents the interbank assets of bank J owned by bank I . a_i and l_j are the sum of each row and column, representing the aggregate claims/liabilities of bank I against all other banks.

$$\text{with } \sum_{j=1}^{N} x_{ij} = a_i \ \sum_{i=1}^{N} x_{ij} = l_j \tag{2.3}$$

Both a_i and l_j can be obtained from the individual bank's balance sheet, but x_{ij} is not observable as no information is revealed on the specific counterparts with which each bank is transacting.

In order to estimate x_{ij}, it is necessary to first assume the distribution of the bilateral exposures. The ME approach starts with the assumption that banks seek to maximize the dispersion of their interbank activity, which means each bank symmetrically holds claims on all other banks in the system. In the terminology of information theory from which ME originates, it amounts to maximizing the entropy of the matrix. This assumption may introduce bias to the simulation result and, as discussed earlier, the direction of bias could be mixed. Given no better choice for the method, this paper follows Sheldon and Maurer (1998) and many others who deal with aggregated data.

$$\sum a_i = \sum l_j = 1 \tag{2.4}$$

By normalizing a's and l's as in equation (2.4), the solution is given by equation (2.5) [3]:

[3] Refer to Sheldon and Maurer (1998), Upper and Worms (2002) and the Appendix in Wells (2004) on how the equation is derived.

$$x_{ij} = a_i \times l_j \tag{2.5}$$

Equation (2.5) implies that the amount that bank *I* lends to bank *J* depends on the share of bank *I*'s total lending to the market and the share of bank *J*'s total borrowing from the market. The approach is sensible because, in reality, large banks normally have a large volume of interbank transactions with their large-sized counterparts. Equation (2.5) also suggests that the ME approach produces a "complete market structure" in that any bank, even borrowing/lending with a small size, will spread their transactions across all banks in the system, i.e. maximisation dispersion. In reality, however, the approach rules out relationship banking, in which banks normally have a few fixed clients with which to transact.

On the main diagonals of the matrix, where $I=J$, x_{ij}'s represent their exposure to themselves. On one hand, it is an appealing result for large banks because the aggregate interbank loans/deposits (represented by the marginal a's and l's) contain intra-group transactions[4]. Similarly, for foreign groups, the x_{ij}'s on the main diagonal denote interbank transactions between foreign banks located in the UK. On the other hand, for independent small or mid-sized banks, this might be an unappealing feature because they do not lend to or borrow from themselves. A restriction that sets those x_{ij}'s to zero has to be imposed on some of the x_{ij}'s that represent ten small and mid-sized banks. Hence, the matrix X^0 is reconstructed with elements expressed as:

[4] See the "Notes to the Accounts" of the consolidated balance sheet of each bank.

$$x_{ij}^0 = \begin{cases} 0 & \forall\, i = j \in small\ \&\ mid - sized\ banks \\ a_i l_j,\ otherwise \end{cases} \tag{2.6}$$

where the expression of x_{ij}^0's for all entries are unchanged from equation (2.6) except for those small and mid-sized banks.

Since the matrix is now inconsistent with the adding up constraints, i.e. a_i's and l_j's, a minimization problem needs to be solved to find a new matrix X^* that gets as close to the matrix X^0 as possible, given the constraints. In information theory, this is termed as cross-entropy minimisation. This problem can be formally written as follows:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} x_{ij}^* \ln\left(\frac{x_{ij}^*}{x_{ij}^0}\right)$$
$$Subject\ \ to \sum_{j=1}^{N} x_{ij}^* = a_i \quad \sum_{i=1}^{N} x_{ij}^* = l_j \tag{2.7}$$

with the convention that $x_{ij}^* = 0$, and only if, $x_{ij}^0 = 0$, and 0ln(0/0)≡0. This matrix is calculated by the RAS algorithm. Although Blien and Graef (1991) and Censor and Zenios (1997) have an exclusive explanation on the RAS, Wells (2004) provides a simple summary of how the algorithm works, given the estimate matrix X^0, as follows:

Step 1 (row scaling): $x_{ij}^{U} \leftarrow x_{ij}^{U} \rho_{ij}^{U}$, $\quad where\ \rho_{ij}^{U} = \frac{a_i}{\sum_{\forall j | x_{ij}^{U} > 0} x_{ij}^{U}}$

Step 2 (column scaling): $x_{ij}^{U+1} \leftarrow x_{ij}^{U} \sigma_{ij}^{U}$, $\quad where\ \sigma_{ij}^{U} = \frac{l_i}{\sum_{\forall i | x_{ij}^{U} > 0} x_{ij}^{U}}$

Step 3: $U \leftarrow U + 1$, and return to step 1.

The new matrix X^*, estimated from the iteration process, is regarded as a benchmark model, a proxy of the complete market structure to be compared later with other market structure simulations.

2.4.4 Simulation, Structures & Results

This section presents the scope of contagion in the UK interbank market, simulated through the contagion mechanism in section 4.1 and relying on the bilateral exposure estimated in section 4.4. As the ME approach used to estimate the bilateral exposure assumes a complete market structure, the section performs a number of sensitivity analyses or places additional restrictions upon the benchmark structure in order to take account of other structures/scenarios. Changes of magnitude in contagion are assessed in various scenarios including intensive transactions within the same bank groups, money centre structure and increasing levels of internationalization.

2.4.5.1 Complete Market Structure

Table 2.5 presents the simulation results under the benchmark complete market structure. The magnitude of contagion is analysed in several ways: cases of contagion out of total scenarios, number of contagious banks, number of failing banks at each round of contagion and assets affected by percentage of total industry assets. The result suggests a wide scale contagion at 100% and 80% LGD, leading to contagious default of 17 banks (excl. the triggering bank), amounting to 89.48% of total assets in the banking sector. The spill-over effect could happen in four out of a total of twenty-one cases. In particular, the triggering banks appear to be either one of the two largest domestic banks or one of the largest foreign groups, one from Other EU countries, the other from Other Developed countries. These four might be the biggest borrowers from the market. In contrast, when the LGD is lowered to 60%, only one case out of 21 would trigger contagion and that case causes the default of nine banks holding 69.45% of total assets. No contagion is found under 40% LGD.

Table 2.3: Magnitude of contagion under benchmark structure

LGD	Cases of contagion (out of 21)	Triggering bank	No. of banks failed at each round of contagion (excluding the initial failure)					
			1st round	2nd round	3rd round	4th round	Total	Assets%
100	4	Large bank 1	1	9	7	0	17	89.48%
		Large bank 2	1	9	7	0	17	
		Other EU	1	12	4	0	17	
		Other Developed	6	10	1	0	17	
80	4	Large bank 1	1	6	9	1	17	89.48%
		Large bank 2	1	6	8	2	17	
		Other EU	1	7	8	1	17	
		Other Developed	4	10	2	1	17	
60	1	Other EU	5	3	1	0	9	69.45%
40	0	-	-	-	-	-	-	-

The interpretation of the round of contagion is different from some of the existing studies, as they conclude that the more rounds involved in the contagion, the worse the magnitude. Their conclusions are based on a large sample of data (e.g. 3,246 banks in Germany) which could generate up to eight rounds in a simulation. In this case, however, the total sample is limited and the simulation generates at most four rounds of contagion. Here, the number of rounds is regarded as the speed of transmitting—under the same scenario, the more rounds, the slower the contagion is to transmit and the more favourable the scenario for regulators to manage crises. Moreover, the number of banks failing at each round of contagion also tells the speed. For example, at 100% LGD, although the total number of banks failing in the end stays the same, the contagion triggered by banks from Other Developed results in a faster transmission than other scenarios, because banks that default in the first round amount to six compared to one in others.

2.4.5.2 Increasing Weights to Intra-group Exposure

As the complete market structure maximizes the dispersion of interbank lending, it neglects the fact that lending/borrowing could be largely resolved within the same bank group. Thus, bias could be created in the contagion simulation. Using unconsolidated data, Wells (2004) tackles this problem through forming a new initial estimate of the interbank structure. If a bank belongs to banking group I, the elements are:

$$x_{ij}^{INTRA} = \begin{cases} (1-\delta)x_{ij}^{0} + \delta \dfrac{x_{ij}^{0}}{\sum\limits_{j=I} x_{ij}^{0}} & \textit{for } j \in I \\ (1-\delta)x_{ij}^{0} & \textit{otherwise} \end{cases} \tag{2.8}$$

He introduces δ to determine the additional weight given to intra-group lending. One extreme, δ = 0, yields the benchmark case. At the other extreme, δ = 1, a bank that belongs to a larger group is assumed to borrow and lend only with other members of the same group.

Inspired by Wells, this chapter alters equation (2.8) to suit the consolidated data as below in equation (2.9). The common nature of equation (2.8) and (2.9) is that, although the distribution of funds in the market has been altered, the total exposure of interbank market remains unchanged, $\sum x_{ij} = 1$.

$$x_{ij}^{INTRANEW} = \begin{cases} (1+\delta)a_i l_j & \forall\, i = j \in A \\ x_{ij}^0 (1+\delta) - \delta \dfrac{x_{ij}^0}{1 - \sum_{i=j\in A} x_{ij}^0} & otherwise \end{cases} \tag{2.9}$$

In the new structure, δ still determines the additional weight given to intra-group lending. Self-exposures of banking group A (here, four large banks) are assigned with more weights $(1+\delta)$, while the rest of the elements ($i = j \notin A$) are weighted down to scale. Since $(1+\delta)a_i$ is between zero and one, the upper and lower bound for δ can be derived[5]. Particularly, if δ =0, it still yields the benchmark model.

The change of contagion impact in increasing intra-group transactions is presented in Table 2.6. The first column lists the value of δ in ascending order, indicating increasing weights assigned to intragroup activities. At each row of a different δ, the magnitude of contagion is measured by the cases of contagion, the number of failing banks at each round of contagion, the total number of contagious banks excluding the initial bank and their assets according to a percentage of total industry assets. All results are based on the worst case scenario (fast transmission) and are presented at 100% LGD.

[5] Choosing the highest a_i, the upper boundary level of δ in this paper is 2.2791.

Table 2.4: Increasing weight to intragroup exposure (Worst Case Scenario, LGD=100%)

δ	Cases of contagion (out of 21 cases)	Number of failing banks at each round of contagion (excluding the initial failure)						Banks failed (excl. initial failure)
		1st round	2nd round	3rd round	4th round	5th round	Total	Assets %
-0.5	4	1	7	8	1	0	17	89.96%
0.1	4	1	5	8	2	1	17	89.96%
0.5	4	1	5	7	3	0	16	89.88%
1	2	1	4	3	1	0	9	69.45%
1.4	1	1	3	3	1	0	8	63.73%
1.7	1	1	3	2	0	0	6	57.29%
1.94	0	0	0	0	0	0	0	-

Table 2.6 implies that a rise in δ from -0.5 to 1.94 increasingly mitigates the magnitude of contagion. The cases of contagion are reduced from 4 to 0; total contagious banks are reduced from 17 holding 89.96% of total assets to no evidence of contagion. For δ's equalling -0.5, 0.1 where there are all four cases out of 21, Table 2.6 suggests that the speed of contagion slows from the second round, with the number of defaulting banks reducing from seven banks ($\delta = -0.5$) to five banks ($\delta = 0.1$).

However, it is worth noticing that this sensitivity analysis cannot be compared with a benchmark structure in the way that the money centre model can in the next section. This is because, by applying equation (9), the restrictions of the matrix have been changed. The amount of aggregate interbank assets (a_i's) and liabilities (l_j's) for each bank diverges from the sample data, although the total exposure ($\sum a_i$ or $\sum l_j$) remains the same. Nevertheless, as long as the relative scale for each restriction does not vary much, the comparison can be made with the benchmark ($\delta = 0$) in terms of assessing contagion risk other than in the year 2004.

2.4.5.3 Multiple Money Centre Structure

The multiple money centre structure assumes a two-tier hierarchical lending system illustrated in Table 2.7. The capital letters are short forms of "Small banks" (S), "Mid-sized banks" (M), "Large banks" (L) and "Foreign banks" (F). It can be seen in the table that intersect values between S and S, M and M, S and M, S and F are zero. This means that, at the bottom level of the hierarchical structure, small and mid-sized banks transact only with large banks and conduct no activities among themselves or with foreign banks[6]. All other cells in the table are filled with 1s, representing transactions between large banks and all banks. Therefore, at the top level of the hierarchical structure, large banks serve as money centres in the system.

[6] A pure money centre structure is constructed to be compared with the complete market structure in contagion analysis. However, the assumption may be slightly divergent from the real market where small and mid-sized banks do transact with each other. Equation (9) allows this feature to be captured by weighting the shares of transactions of small banks. Higher weights are assigned to the transactions of small banks with large banks while lower shares represent transactions among small banks.

Table 2.5: Matrix of money centre structure

	S	M	L	F
S	0	0	1	0
M	0	0	1	0
L	1	1	1	1
F	0	0	1	1

Note: S, M, L, F denote small, mid-sized, large and foreign-owned banks respectively. "1" and "0" means transaction and no-transaction between two banks.

Technically, a money centre matrix is constructed by placing an extra zero into the initial matrix X^0 as follows:

$$x_{ij}^0 = \begin{cases} 0 & \forall\, i = j \in small\ \&\ mid-sized\ banks \\ 0 & \forall i \in small\ banks\ and\ j \notin large\ banks \\ 0 & \forall i \in mid-sized\ banks\ and\ j \notin large\ banks \\ a_i l_j, & otherwise \end{cases} \quad (2.10)$$

Then, the RAS algorithm is applied again to minimise the distance between X^0 and X^* (refer to equation 2.7). The estimated elements in X^* will go through the contagion mechanism.

Table 2.8 presents the magnitude of contagion under a money centre structure, which can be compared with the benchmark complete market structure. In the worst case scenario, the two structures are equivalent in the total number of contagious banks, 17 banks at both 100% and 80% LGD, nine banks and zero banks respectively for 60% and 40% LGD. However, in general, it is hard to judge whether the complete structure or money centre structure is more contagious from the simulation test. On the one hand, the average number of total banks affected under the money centre structure is less than the complete market structure (e.g., 15 banks for two scenarios under a money centre structure vs. 17 for all scenarios under a complete market structure at LGD=100% and 80%). This suggests a lower possibility of severe contagion in a money centre model. On the other hand, a money centre structure appears to be slightly more contagious in terms of cases of contagion. At LGD=60%, one more scenario triggered by banks owned by other developed countries could cause contagion under a money centre structure.

Table 2.6: Magnitude of contagion under a money centre structure

LGD	Cases of contagion (out of 22)	Scenario	No. of failing banks at each round of contagion (excl. the initial failure)					
			1st round	2nd round	3rd round	4th round	5th round	Total
100	4	Large bank 1	1	7	7	0	-	15
		Large bank 2	3	6	6	2	-	17
		Other EU	1	6	8	2	-	17
		Other Developed	4	7	6	0	-	17
80	4	Large bank 1	1	6	8	0	-	15
		Large bank 2	1	7	6	2	-	16
		Other EU	1	5	5	6	-	17
		Other Developed	3	5	3	6	-	17
60	2	Other EU	1	2	3	1	0	7
		Other Developed	1	1	3	3	1	9
40	0	-	-	-	-	-	-	-

When comparing the number of banks at each round of contagion in both models, it seems that the money centre model is slower in transmission speed, as more banks fail in the 3rd round rather than in the 2nd round in the benchmark model. This is because the money centre structure assumes no transactions between small or mid-sized banks and foreign banks; it is assumed that transactions only occur with money centre banks. When the triggering banks are foreign bank groups, the contagion will not be transmitted quickly until a money centre bank defaults.

2.4.5.4 Increasing Weights to "Foreign Exposures"

According to the Bank of England and Wells (2004), 75% of total interbank lending consists of transactions between UK resident banks and non resident banks. However, due to data limitation, Wells (2004) simulates contagion of UK resident banks using interbank lending data containing a large share of cross-border exposure. As discussed earlier in section 3.2.1, this amounts to spreading large cross-border exposures into the domestic market, creating a serious bias in the simulation results.

Although restricted by the same data problem, this chapter is able to fix the bias by increasing the proportion of interbank exposure of domestically owned banks with foreign-owned banks. The process can also be regarded as a sensitivity analysis in order to assess the scope of contagion in increasing internationalization. As illustrated in Table 2.9 below, the cells representing bilateral exposures x_{ij} of banks of different types vary in shading. The darkly shaded parts represent more weights assigned to all exposures to foreign banks (denoted by "H") while other squares in lighter shading mean transactions are weighted down to scale.

Table 2.7: Matrix of for internationalization analysis

	S	M	L	F
S				
M				I
L				
F		I		

Note: S, M, L, F denote small, mid-sized, large and foreign-owned banks respectively. The darkly shaded squares represents more weights assigned to transactions with foreign banks, while the lighter shaded squares mean transactions are weighted down to scale.

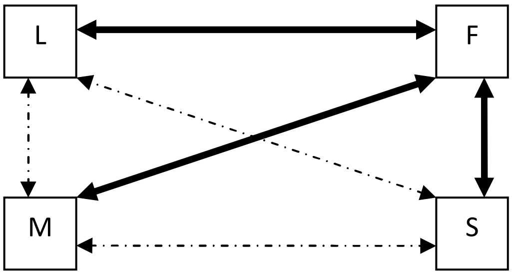
Formally, Table 2.9 can be formulated as follows:

$$x_{ij}^{INTL} = \begin{cases} (1-\mu)x_{ij}^{0} + \mu \dfrac{x_{ij}^{0}}{\sum_{i \in I} \sum_{j \in I} x_{ij}^{0}} & \textit{for } i, j \in H \\ (1-\mu)x_{ij}^{0} & \textit{otherwise} \end{cases} \tag{2.11}$$

where μ denotes the additional weight given to transactions with foreign banks. One extreme, μ = 0, yields the benchmark case. At the other extreme, μ = 1, no lending is made domestically, all transactions take place with foreign banks. Equation (2.11) is an application of Wells' equation (2.8) in a different way.

The test is based on two initial structures: the benchmark structure and the money centre structure; hypotheses can be made before the simulation. Figure 2.10 and Figure 2.11 plot the two structures showing increased levels of internationalization which are denoted by bold arrows. Based on the benchmark complete market structure in Figure 2.10, the scope of contagion will increase with internationalization, because the market becomes more consolidated with foreign banks than previously.

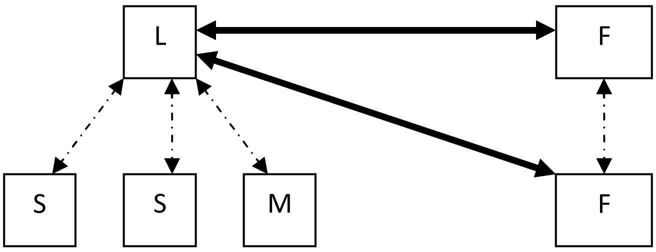
Figure 2.8: Increasing weights to "foreign exposure" in benchmark structure



Note: S, M, L, F denote small, mid-sized, large and foreign-owned banks respectively. Bold arrows denote intensive transactions, while the dashed arrows denote fewer transactions.

However, based on the money centre structure in Figure 2.11, raising the level of internationalization will decrease the severity of contagion, because the exposure levels of the money centre banks become more diversified.

Figure 2.9: Increasing weights to "foreign exposure" in a money centre structure



Note: S, M, L, F denote small, mid-sized, large and foreign-owned banks respectively. Bold arrows denote intensive transactions, while the dashed arrows denote fewer transactions.

The results of the sensitivity test are displayed in the following two tables. Generally, they are consistent with the two hypotheses stated above. Table 2.10 and Table 2.11 are respectively based on the complete market structure and the money centre structure under worst case scenarios at 100% LGD level. The magnitudes of contagion are measured for μ ranging from 0 to 1, representing increasing levels of internationalization.

Table 2.8: Increasing internationalization in a benchmark structure (Worst Case Scenario, LGD=100%)

μ	Cases of contagion (out of 21 cases)	Number of failing banks at each round of contagion (excluding the initial failure)					Banks failing (incl. initial failure)
		1st round	2nd round	3rd round	4th round	Total	Assets%
0	4	4	10	2	1	17	86.0345%
0.2	4	4	4	8	1	17	86.0345%
0.4	3	4	3	9	1	17	86.0345%
0.6	3	5	8	4	0	17	86.0345%
0.8	4	9	5	3	0	17	86.0345%
1	4	11	4	2	0	17	86.0345%

Table 9 suggests that, in general, the contagion impact does not change significantly for different μ. The total number of contagious banks remains the same and so does the same share of total banking assets. However, when μ arises, an increasing number of banks default at the first round of contagion. This implies that the speed of contagion increases when the market evolves to become concentrated on foreign banks which function as money centres. Based on the money centre structure, Table 7 indicates a decrease in the magnitude of contagion, though not significantly. The total number of bank failures, excluding the initial collapse, fall from 17 to nine. Assets affected as a percentage of the total diminish from around 95% to 84%.

Table 2.9: Increasing internationalization in the money centre structure (Worst Case Scenario, LGD=100%)

μ	Cases of contagion (out of 21 cases)	Number of failing banks at each round of contagion (excluding the initial failure)					Banks failing (incl. initial failure)
		1st round	2nd round	3rd round	4th round	Total	Assets%
0	4	3	5	3	6	17	94.9962%
0.2	4	3	5	3	5	16	89.8773%
0.4	4	2	3	5	1	11	84.9685%
0.6	3	3	4	2	1	10	84.2440%
0.8	4	4	5	0	0	9	84.2436%
1	4	5	4	0	0	9	84.2436%

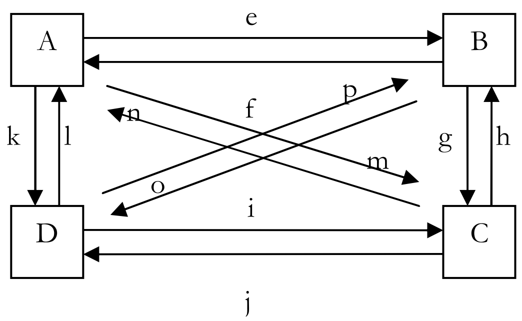
2.4.5 Consolidated vs. Unconsolidated Exposure: a Four-Bank Illustration

Simulation results in the previous sections demonstrate wide scale contagion in the 2004 UK interbank market. At 100% LGD of benchmark structure, the failure of a large domestic bank or a foreign bank group could cause contagious default of banks holding 89.48% of total industry assets. However, the magnitude is four times higher than that in the benchmark structure of Wells (2004), in which only 25.25% assets are affected.

As discussed earlier, the consolidated data could be the major source of the divergence as Wells (2004) uses unconsolidated data to estimate the consolidated contagion impact.

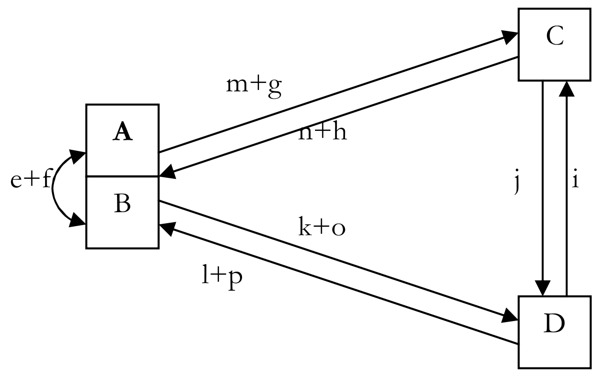
According to International Accounting Standards rule 27 (IAS 27), consolidated financial statements present financial information about a parent's undertakings and its subsidiary undertakings as a single economic unit, while unconsolidated statements present them as separate units. The differences in interbank exposure between consolidated and unconsolidated reporting are illustrated in a pseudo-four-bank interbank system. Figures 2.8 and Figure 2.9 represent two interbank markets comprising the same bank entities. Bank A and bank B are the only two subsidiaries under the group AB while bank C and bank D are independent institutions[7]. However, group AB is reported in an unconsolidated way in Figure 2.8 and is regarded as two separate entities, while it is reported as one in Figure 2.9. It assumes that the bilateral interbank exposure of and between the four banks is known and denoted by lower case letters. Both interbank markets are equalized in aggregate liquidity demand and cash excess, i.e. the total volume of interbank transactions e+f+g+h+i+j+k+l+m+n+o+p is same for Figure 2.8 and Figure 2.9.

Figure 2.10: Interbank positions of unconsolidated exposure



[7] Consolidated and unconsolidated statements, according to accounting standards, only refer to the financial statement of the bank group (bank C and bank D combined). Independent institutions (bank C and bank D) that neither govern nor are controlled by another entity do not have to show their financial statements in several ways.

Figure 2.11: Interbank positions of consolidated exposure



Most studies use unconsolidated balance sheets, which imply in Figure 2.10 that they regard the transactions of bank A and bank B with other banks as separate. However, the simulation in this chapter, using consolidated balance sheets, regards all the transactions of the group as being carried out by a single equivalent company. Thus, the exposure of bank A and bank B to bank C in Figure 2.10 is "m" and "g" respectively, while the exposure of the bank group AB to bank C is "m+g" in Figure 2.11. It can also be seen that the interbank structure using unconsolidated data is more complete, while the structure using consolidated data is more concentrated. It is clear from a simple simulation which is more contagious in magnitude. The assets and Tier-1 capital of each individual bank are first denoted as:

Tier 1 of A= α Assets of A=a

Tier 1 of B= β Assets of B=b

Tier 1 of C= γ Assets of C=c

Tier 1 of D= λ Assets of D=d

Applying the contagion mechanism of condition (1), the simulation result is displayed in Tables 2.2 and 2.3. The first row of both tables lists four scenarios, with each bank denoted as the triggering bank. Cells under each scenario (excl. the last row) indicate the contagion condition for banks other than the triggering bank. θ's represent LGD rates. The last row shows the assets affected under the worst case scenario, i.e. all banks fail in the first round of contagion.

Table 2.10: Contagion simulation using unconsolidated exposure

	Bank A	Bank B	Bank C	Bank D
Bank A fails if	-	$e\theta > \alpha$	$m\theta > \alpha$	$k\theta > \alpha$
Bank B fails if	$f\theta > \beta$	-	$g\theta > \beta$	$o\theta > \beta$
Bank C fails if	$n\theta > \gamma$	$h\theta > \gamma$	-	$j\theta > \gamma$
Bank D fails if	$l\theta > \lambda$	$p\theta > \lambda$	$i\theta > \lambda$	-
Assets affected in worst case scenario	b+c+d	a+c+d	a+b+d	a+b+c

Table 2.11: Contagion simulation using consolidated exposure

	Bank Group AB	Bank C	Bank D
Bank AB fails if	-	$(m+g)\theta > \alpha + \beta$	$(k+o)\theta > \alpha + \beta$
Bank C fails if	$(n+h)\theta > \gamma$	-	$j\theta > \gamma$
Bank D fails if	$(l+p)\theta > \lambda$	$i\theta > \lambda$	-
Assets affected in worst case scenario	c+d	a+b+d	a+b+c

From the simulation, it seems that the banking system using consolidated exposure is more likely to experience contagion than the system using unconsolidated exposure. This is because the average interbank exposure to the system, relative to Tier-1 capital using consolidated exposure, is larger than using unconsolidated exposure or:

$n + h > n \qquad n + h > h$

$l + p > l \qquad l + p > p$

$m\theta > \alpha \;\&\; g\theta > \beta \Rightarrow (m + g)\theta > \alpha + \beta \quad but\ not\ vice\ versa$

$k\theta > \alpha \;\&\; o\theta > \beta \Rightarrow (k + o)\,\theta > \alpha + \beta \quad but\ not\ vice\ versa$

However, many studies measure contagion by assessing assets affected as a percentage of total assets in the system. If the triggering bank is an independent bank like bank C or bank D, there is no difference in magnitude of contagion between consolidated and unconsolidated exposure. If the triggering bank is bank A or bank B, which are treated as an independent bank in Figure 2.10, but single entities in Figure 2.11, chances are that unconsolidated exposure is more contagious following the default of bank A or bank B in Table 2.2, because:

$$\frac{b+c+d}{a+b+c+d} > \frac{c+d}{a+b+c+d} \qquad and \qquad \frac{a+c+d}{a+b+c+d} > \frac{c+d}{a+b+c+d}$$

In that case, it is interesting to point out that the simulation results depend heavily on the Tier-1 capital of the existing banks following an idiosyncratic shock with LGD at 100%:

$(i) \quad c_i < x_{i\_Uncon} \quad \Rightarrow Unconsolidated\ exposure\ more\ contagious$

$(ii) \quad x_{i\_Uncon} < c_i < x_{i\_Con} \Rightarrow Consolidated\ exposure\ more\ contagious$

$(iii)\ c_i > x_{i\_Con} \Rightarrow No\ contagion\ in\ both\ systems$

c_i denotes the Tier-1 capital of banks in the system other than the triggering bank (three cases, A fails, B fails or AB fails). If the Tier-1 capital of each existing bank is less than its exposure to the triggering bank using unconsolidated reporting, or denoted as x_{i_Uncon}, the system of unconsolidated exposure (Figure 2.10) is more contagious than that of consolidated exposure (Figure 2.11); If the Tier-1 capital of each existing bank is more than x_{i_Uncon}, but less than x_{i_Con}, the exposure to the triggering bank using consolidated reporting, the system of consolidated exposure is more contagious; if the Tier-1 capital is adequate for each bank and greater than x_{i_Con}, both systems in Figure 2.8 and Figure 2.9 are robust to the shock and no contagion exists. If each bank has its Tier-1 capital within a different range, for example bank I within range (i) and bank J within (ii), it cannot determine a priori which system is more contagious.

Another interesting finding from the simulation is that the intra-group transaction (amounting to e+f) is irrelevant[8] to the contagion analysis under consolidated reporting, since it assumes that all subsidiaries stand and fall together as a single entity. Therefore, it is not important to know which subsidiary, bank A or bank B, takes control in the group, in addition to the seniority of interbank loans within the group.

[8] It is relevant, however, if the bilateral position is not known and has to be estimated. The following sections will explore how the change of estimated intragroup exposure will affect the severity of contagion.

2.4.6 A Historical Comparison

The author also investigates the inconsistency in results by simulating the contagion effect prior to 2004. This is because the possibility exists that the magnitude of contagion has been increasing over time since 1999, the year on which Wells' study (2004) is based. As most small and mid-sized banks did not release their annual reports prior to 2002 when they become publicly limited companies, the oldest year it is possible to simulate is 2002.

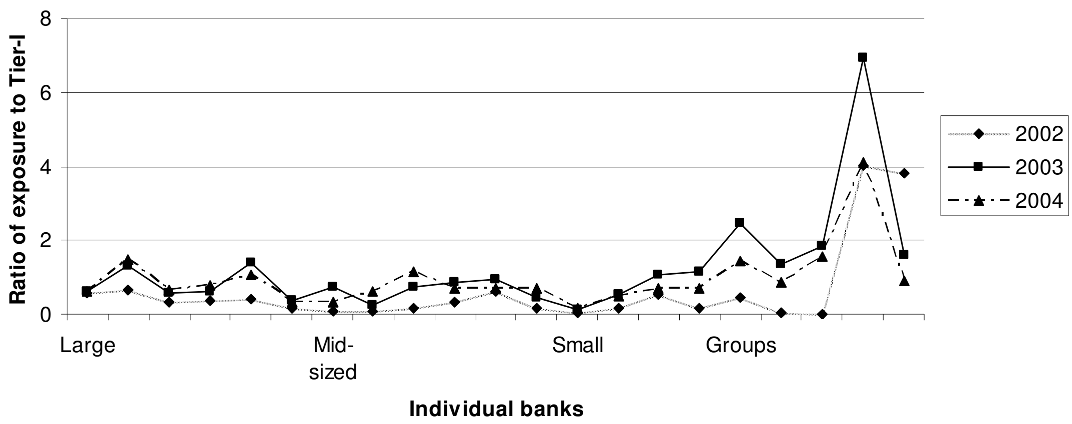
Simulation results from 2002 to 2004 are displayed in Table 2.12. It can be seen that the scale of contagion in 2003 is close to that of 2004. Eighteen banks in the system are affected, accounting for 98.70% of the total for both 80% and 100% LGD. In 2002, however, the scale is quite limited, with only 12.57% of assets being affected.

Table 2.12: Magnitude of contagion in the benchmark structure in 2002 and 2003

<table>
<tr><th></th><th colspan="3">2002</th><th colspan="3">2003</th><th colspan="3">2004</th></tr>
<tr><th>LGD</th><th>Cases of contagion</th><th>Total No. failed</th><th>Assets %</th><th>Cases of contagion</th><th>Total No. failed</th><th>Assets %</th><th>Cases of contagion</th><th>Total No. failed</th><th>Assets %</th></tr>
<tr><td>100</td><td>11</td><td>2</td><td rowspan="4">12.57%</td><td>7</td><td>18</td><td rowspan="2">98.70%</td><td>4</td><td>17</td><td rowspan="2">89.48%</td></tr>
<tr><td>80</td><td>7</td><td>2</td><td>5</td><td>18</td><td>4</td><td>17</td></tr>
<tr><td>60</td><td>6</td><td>2</td><td>5</td><td>9</td><td>67.37%</td><td>1</td><td>9</td><td>69.45%</td></tr>
<tr><td>40</td><td>3</td><td>2</td><td>0</td><td>0</td><td>-</td><td>0</td><td>0</td><td>-</td></tr>
</table>

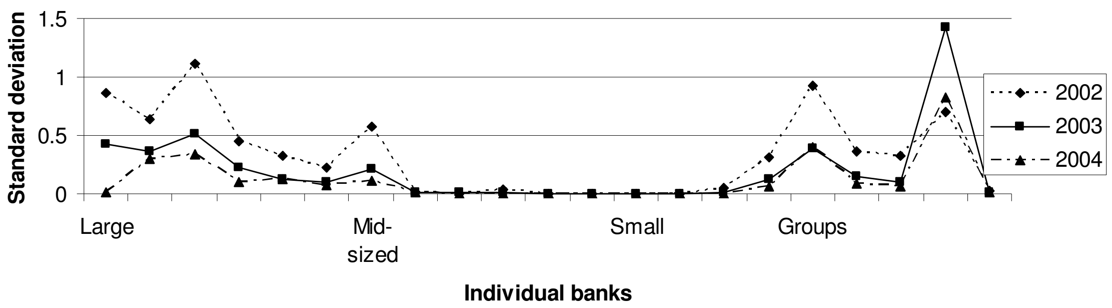
The reason for a greater magnitude in 2003 is revealed in Figure 2.12. The ratio of maximum exposure of each bank i.e. x_{ij} to its Tier-1 capital, is relatively higher in 2003 (and lower in 2004) than other years. This means that, in 2002, banks were more vulnerable to the credit shocks of their largest borrower due to a relatively lower capital ratio.

Figure 2.12: Ratios of interbank exposure to Tier-1 capital (maximum value)



However, it is interesting to find that the year that suffers the least number of spill-out effects also experiences the most cases of contagion, i.e. 11 out of 21 scenarios in 2002 under 100% LGD. In 2003, the number of cases was seven, while in 2004 the number of scenarios was four. For all other LGD, 2004 experiences the lowest number of cases of contagion. These findings are associated with the concentration of interbank loans over the period, which is shown in Figure 2.13. Except for small banks and one foreign group, the standard deviation of the ratio of interbank exposure to Tier-1 capital across banks is highest in 2002 and lowest in 2004. This implies systemically, the interbank exposure is more concentrated in a few banks in 2002 than other two years.

Figure 2.13: Ratios of interbank exposure to Tier-1 capital (standard deviation)



Additionally, the section also investigates interbank contagion following a system-wide shock which can be simulated by multiple bank failures. Table 2.13 presents, for each bank, the possibility of joint default of all borrowers. Here, if the ratio of the total interbank loans of a bank $\sum_{j}^{N} x_{ij}$ to its Tier-1 exposure exceed 1, the bank will become bankrupt at LGD=100%. If the ratio is less than 1, the bank could survive the shock. It can be seen from the table that nine out of 21 banks could survive in 2002, while the number is reduced to two banks in 2003 and 2004, suggesting overall that banks tend to be increasingly susceptible to common macroeconomic shocks.

Table 2.13: Ratios of interbank exposure to Tier-1 capital (joint default)

	2002	2003	2004
1	3.621348	1.768707	1.85268
2	3.979546	3.904361	4.509123
3	1.930065	1.662361	1.942208
4	2.419217	1.765794	2.361932
5	2.571335	4.126534	3.175809
6	0.939139	1.093311	1.007547
7	0.558321	1.954728	0.971055
8	0.51847	0.758224	1.818423
9	1.07521	2.187835	3.42283
10	2.067541	2.574968	2.143719
11	3.734232	2.724283	2.107269
12	0.877676	1.34215	2.060926
13	0.287979	0.302746	0.434678
14	0.939083	1.534502	1.439389
15	3.206469	3.164737	2.105121
16	0.992714	3.415251	2.127453
17	2.745744	7.281425	4.36928
18	0.136692	4.024392	2.647914
19	0.014704	5.460723	4.689732
20	25.13567	20.38998	12.31786
21	23.71094	4.739103	2.72376

2.5 Conclusion

Netting obligations pose contagion risk to all economic sectors when one or multiple obligors in the netting system are unable to make repayments. In manufacturing, the risk lies in the trade credit which links producers through a chain of obligations, and in the insurance industry the propagation could spread through the line of reinsurance. Similarly, in banking sectors, the risk exists in interbank lending in which the transactions are often not collateralized or insured against. Regulators anxiety, however, is perhaps strongest regarding the banking sector, because it has vital connections with other sectors and interbank exposure is increasingly forming a large proportion of banks' balance sheets.

The chapter reviewed studies conducted by central banks of different countries that simulate the contagion risk in the interbank market. It found that the severity of contagion impact is subject to various "conditions"/assumptions, making the interpretation of contagion subject to important caveats. By analyzing a number of potential sources of bias, the author found that it is not possible to determine a priori whether these biases result in an overestimation or an underestimation of contagion.

Among the source of bias, the chapter is particularly interested in the impact of using consolidated data vs. unconsolidated data. This is because most of the existing studies use the latter to simulate interbank contagion, in which the structure of which is close to a complete market structure. However, their results could significantly distort the real picture of contagion effect because for many countries, the banking sectors are normally highly concentrated with large bank groups owning a significant number of subsidiaries. And it is most likely that mother banks and their subsidiaries stand or fall together.

Subject to a number of assumptions (no netting agreement, seniority, etc), the author assesses the contagion effect of the UK interbank market in 2004, and found the spill-over scenarios are usually triggered by large banks that have the most exposure to the market. This supports the "too-big-to-fail" theory that many central banks are concerned about when a big bank is endangered. More importantly, the author found that the contagion is much severer if the simulation uses consolidated data (89.48% assets affected) than otherwise (unconsolidated data) in the existing studies (25.25% assets affected). The difference has been explained in a 4 bank illustration. First, simulation using consolidated exposure is more likely to trigger contagion in a system of unconsolidated exposure than that of consolidated exposure, because the average interbank exposure relative to tier-I capital is larger in the system of consolidated exposure than that of unconsolidated exposure. Second, if the contagion impact is measured by the percentage of total banking sector assets, the author demonstrates that simulation using consolidated exposure is more contagious when the average capital position is between the consolidated interbank exposure and the unconsolidated exposure.

As the result of existing studies is based on years before 2004, the chapter also investigates if the scope of contagion has changed over time. Due to data limitation, the chapter simulates the contagion impact for only two years before 2004. The results show a similar contagion impact between 2003 and 2004 in terms of the percentage of total banking sector assets affected. The effect of 2002 is quite limited, accounting for only 12.57%. The statistics of an increasing ratio of the interbank exposure over Tier-1 capital also imply that the contagion impact could increase rapidly since 2000 from which Wells (2004) has conducted the simulation on UK.

Moreover, the Entropy Maximization method has to be used to estimate the bilateral interbank exposure due to data limitations. The method assumes that banks seek to maximize the dispersion of their interbank activity and has the drawback of neglecting relationship banking. The author deals with the drawbacks of ME by manually changing the weights of interbank exposure between intra-group banks, or between money centre banks and small banks, or between domestic banks and foreign banks. The results show that encouraging intra-group financing could effectively alleviate the potential systemic risk while increasing interbank transactions with foreign banks in a highly concentrated market like UK could facilitate diversification and enhance financial stability.

CHAPTER THREE

TESTING INTERBANK MARKET DISCIPLINE IN THE UK

3.1 Introduction

The role of market discipline has become increasingly important as the banking industry has grown more complex. Unlike government discipline, in the form of regulation, the effectiveness of market discipline is characterized by strong built-in incentives that promote safety and soundness in banks. Market discipline literature generally study the disciplinary role of the bond or equity market (Morgan and Stiroh 2001; Sironi 2002; Evanoff and Wall 2002; and Ashcraft forthcoming). However, this chapter focuses on the interbank market, where investors are the banks themselves and the underlying discipline is peer monitoring.

Some of the early studies in this area equate the risk sensitivity of investors to market discipline (Furfine 2001; King forthcoming; Ashcraft and Bleakley 2006). The significance of their test results proves that investors can monitor and rationally differentiate the risks undertaken by banks. Other studies examine this subject from another direction, i.e. the effectiveness of market monitoring. Dinger and Hagen (2008), for example, test whether banks with more interbank borrowing are characterized by lower levels of risk.

However, this chapter redefines the conditions of interbank market efficiency and argues that, to verify market discipline, one should verify both the risk sensitivity of the investors and the effectiveness of their risk control. This is because, on the one hand, risk sensitivity does not guarantee market discipline. The test of Furfine (2001) and others cannot verify if the risk sensitivity of lending banks can influence the decisions of borrowing banks to take more risk. On the other hand, without first confirming the monitoring incentive of the lenders, the negative correlation found in Dinger and Hagen (2008) between the riskiness of banks and their interbank borrowing position could be spurious.

Hence, this chapter examines both aspects of market discipline. This is achieved by performing a Granger Causality test on 12 major UK banks between a number of risk variables and banks' interbank borrowing position. If the riskiness of a bank Granger causes its access to interbank funding, the market is risk sensitive and is monitoring risk. Given the confirmed risk sensitivity, the increasing net interbank position (NIP) of the borrowing banks implies increasing the monitoring incentives of the lending banks. If the lending bank's monitoring incentives Granger causes bank's riskiness, it is very likely that the interbank market disciplines banks. In addition, as the Granger causality test is performed on individual banks[9], this chapter repeats the test on panel data by using least-squared regression. The results are consistent with the Granger test.

The empirical results give little support to the hypothesis of interbank market discipline in the UK. Specifically, it finds both low risk sensitivity and ineffectiveness of risk control. The weak risk sensibility in the UK market is compared to CEE countries studied by Dinger and Hagen (2008), who find strong evidence of market discipline. However, the author find that the nature of the two interbank markets is different. While the net interbank borrowers in CEE countries are all small banks, the major borrowers in the UK are large institutions. Peer monitoring incentives could therefore be dampened if the

[9] The limitations of applying the panel causality test based on existing literature will be analyzed in section 3.2.1.

interbank lenders assume "too-large-to-fail". In addition, lender accountability requires interbank loans to be medium-/long-term so that lenders cannot fly by night and escape their monitoring obligations. However, in contrast with CEE countries, the majority of interbank transactions in the UK market are short-term (mostly less than three months).

Moreover, the chapter explains the results of "risk sensitive but ineffective risk control" in a simple theoretical model. In particular, the model assumes four types of assets in a bank's investment portfolio: "good", "bad", "long-term" and "short-term". Lenders of the interbank transactions are presumed to monitor the riskiness of banks by requiring higher repayment for "bad" assets than "good" assets. Based on four scenarios of repayment described later, the model demonstrates that, even with peer monitoring, banks financed by an interbank fund could choose a riskier asset portfolio to maximize their net expected return. This happens if the "bad" assets are much riskier than the "good" assets and if the probability that both "bad" assets and "good" assets will be repaid is very small. Under the same circumstances, the model demonstrates that banks that have a higher share of short-term interbank borrowing could take more risk.

The remainder of the chapter is structured as follows. Section 3.2 reviews early studies on interbank market discipline and their limitations; it then presents a redefinition of market discipline. Section 3.3 presents an empirical study of the UK interbank market, using both the Granger causality test and least squared regressions. Sections 3.4 and 3.5 explain the results found in Section 3.3. Respectively, Section 3.4 investigates the reason for the weak risk sensitivity of the UK market, compared with CEE countries; section 3.5 establishes a theoretical model to propose a possible explanation for the ineffectiveness of risk control. Section 3.6 concludes.

3.2 Interbank Market Discipline: Literature Review

Interbank exposures have largely been discussed in the literature as a source of contagion (see Chapter Two) and, accordingly, a factor increasing systemic risk. However, Rochet and Tirole (1996) argue that, by generating incentives for peer monitoring, the existence of interbank exposure may also facilitate prudent market behaviour and reduce the risk of bank failure and systemic distress. This is because banks possess the technology to differentiate the risks of other banks (Calomiris, 1998). Given proper incentives, they would peer-monitor each other. Rochet and Tirole (1996) suggest that such incentives are compatible with protecting central banks from undesirable interventions that could lead to moral hazard.

To test the theory of Rochet and Tirole (1996), some of the empirical works evaluate the risk sensitivity of lending banks (Furfine, 2001; King, forthcoming; Ashcraft and Bleakley, 2006). Specifically, they examine how a borrowing bank's access to the interbank market (non-price rationing), or the pricing of its interbank funding is affected by its credit-worthiness. Furfine (2001) finds that borrowing banks with higher profitability, a higher capital ratio, and fewer problem loans pay a lower rate of interest on US federal fund loans than others. Covering a longer and larger cross section, King (2004) supports Furfine's results and finds that risky banks pay a higher rate of interest on US federal funds. He examines, in addition, quantity rationing in response to the riskiness of banks and finds that high-risk banks borrow less from federal funds. However, the impact found in both Furfine (2001) and King (2004) is limited. In Furfine's study (2001), a one standard deviation rise in the loan-to-capital ratio raises the interest rate by merely 1.5 basis points; in King's study (2004), a ten-percentage-point increase in the probability of bank failure leads to a rise of only three basis points in the fed-funds rate. More importantly, monitoring incentives found in those studies are not equivalent to "market disciplines", because it is not clear whether the monitoring incentives discovered have any influence on banks' decisions to take risks.

In contrast, other studies such as Dinger and Hagen (2008) test the interbank market discipline by examining the effectiveness of market monitoring in Central and Eastern European (CEE) countries. They assume that the monitoring incentives of lenders are increasing with the amount of interbank borrowing. Therefore, they examine whether banks with more interbank borrowing are characterized by lower levels of risk. Their results show that interbank borrowing is associated with substantially lower risk with regards to borrowing banks. Specifically, an increase in interbank exposure from zero to 0.1 is associated with a drop in the ratio of loan loss provisions to gross loans of almost 48%, implying strong market discipline in CEE countries. However, the result has an important caveat. The monitoring incentives of lenders are assumed and have not been empirically proved. Without first confirming the monitoring incentives of the lenders, the negative correlation between the riskiness of banks and their interbank borrowing position could be spurious.

3.3 Empirical tests on the UK interbank market

Given the limitations of the existing literature explained in the previous section, this chapter argues that a single test of risk sensitivity or effectiveness of risk control is not sufficient to evaluate "market discipline". Furthermore, this section redefines "market discipline" by considering the following four scenarios in an interbank market:

Case 1: Risk sensitive, Effective risk control

Case 2: Risk sensitive, Ineffective risk control

Case 3: Risk insensitive, Ineffective risk control

Case 4: Risk insensitive, Effective risk control

Case 2 and Case 4 respectively represent possible test results of Furfine (2001) and Dinger and Hagen (2008), which together with Case 3, cannot confirm the hypothesis of market discipline. The only scenario that can confirm the hypothesis is Case 1. This means that investors' risk sensitivity and their effectiveness in terms of risk control are complementary factors of market discipline and should both be tested. Based on the "redefinition" of market discipline, the section establishes a two-step procedure to test empirically the UK interbank market discipline:

Step 1: Test risk sensitivity, i.e. lending banks price risk or ration more risky banks. If the test shows a negative result, it concludes "no market discipline"; otherwise, the test proceeds to Step 2.

Step 2: Test the effectiveness of risk control. If the test shows a negative result, it concludes "no market discipline"; otherwise, it concludes "market discipline".

As available data on individual risk pricing is limited, the test in step 1 examines only risk rationing. Specifically, risk rationing is reflected in the change of borrowing banks' access to the interbank market in response to its riskiness. Section 3.3.1 measures access by net interbank lending position (NIP) and the borrowers' riskiness by a number of risk factors. In Step 1, NIP is dependant variable, while one of the risk measures is explanatory variable and vice versa in Step 2. Section 3.3.2 applies the Granger test to evaluate the two-way causality between NIP and bank riskiness. Section 3.3.3 uses least squared regression to repeat the test on panel data.

3.3.1 Data and risk measurement

The empirical study employs 12 major UK resident banks which cover 70% of the total assets of the UK banking sector. As described in the following two sections, the risk variables are calculated either from the 1995-2007 annual reports of these banks or from their stock market prices from 2001 to 2007[10]. NIP is defined as the ratio of net interbank liabilities to total assets, which is also selected from 1995-2007 banks' annual reports. If

[10] Many banks became public limited companies in the late 1990s.

the NIP ratio has positive/negative values, the bank is a net borrower/provider in the interbank market. Both NIP and risk measurements are in the form of percentage change over the previous period.

3.3.1.1 Risk Measurement Based on SEER Rating Systems

The chapter uses different risk measurements to evaluate banks' credit-worthiness. First, it calculate the over-all riskiness of a bank, designed to encompass all risk taking activities, including the risk of both on-balance-sheet and off-balance-sheet activities, and its chosen capital-to-assets ratio. The over-all risk is based on the variability of bank stock return over time. In particular, it is calculated as the annualized standard deviation of weekly stock return for a given bank in a sample year. The stock market data are chosen because they are more easily accessible than regulatory data such as CAMELS, SEER or private ratings such as Standard & Poor's, Moody's and Fitch Ratings. Nevertheless, they contain the same information as those ratings, which reflect changes in the market's perception of future profitability. Thus, high standard deviations in the return imply that the expected profits of a bank are fluctuating rapidly---a sign that the bank is pursuing risky activities. Second, the chapter evaluates banks' specific risk based on some of the components of the SEER rating system: asset quality, capitals, and earnings. The risk decomposition has the advantage of identifying the particular risk factor the lending banks are sensitive to in Step 1; and how the lenders' accountability works through individual risk components in Step 2.

However, as shown in Table 3.1, the chapter replaces all variables in the SEER rating system by loan loss provision to gross loan ratio (LLP)[11] to measure asset quality. LLP represents estimated credit losses for total bank loans of the current balance sheet date, implying potential risk that has not been realized within the current accounting period. Assuming a similar accounting policy to calculate provisions over the sample period, a higher LLP ratio implies higher credit risk. The chapter does not use the same categories of "Loans 30-90 days past due", "Loans past due 90+ days", and "Nonaccrual loans" as SEER alternatives because they reveal information from a previous accounting period and thus muddle the relationship under question. It is implausible that new interbank lending has any impact on existing bad loans. Similar consideration applies to whether to use net charge-offs to gross loans, accumulated loan loss reserves to gross loans to evaluate asset quality (applied in Dinger and Hagen, 2008). In addition, "Other real estate owned", "Commercial & industrial loans" are considered in SEER to have a negative effect on banks' asset quality. They are not used in this chapter, considering the bias they may cause. The greater in size of those two assets does not necessarily deteriorate total asset quality if banks diversify the risk properly through various industrial sectors. Moreover, "Residential real estate loans" is considered in SEER to have a positive effect on banks' asset quality. However, the chapter argues that it could also have a negative effect when the macroeconomic condition becomes worse, e.g. during the current sub-prime crisis.

Same as in SEER, banks' capital positions and earning abilities are measured respectively by capital to asset ratio (CAR) and net income to asset ratio (ROA), which have a positive

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[11] The chapter assumes LLP has a literal meaning, although provisions for bad loans are sometimes used by banks to smooth earnings.

effect on a bank's riskiness. However, "Investment securities" and "Large time deposits" are replaced by cash-to-asset ratio (LAR) largely due to data availability.

Summary statistics describing the risk variables based on SEER ratings appears in Table 3.2. Panel (a) presents the average values over the sample period, while panel (b) presents summary statistics of total observations. All risk variables are in the form of percentage change. As the table indicates, most risk variables do not display trends over 1996-2007, except for CAR which generally appears to decrease over time. Considerable variability in risk taking exists among banks in the sample. For example, LLP averages -29.46 percent in the sample, but ranges from -1589.92 percent to 763.06 percent.

3.3.1.2 Risk Components Based on Factor Model

A second line of risk decomposing follows Demsetz, Saidenberg, and Straban (1996). As explained in the previous section, overall risk is measured by annualized standard deviation of weekly stock return for a given bank in each sample year. The risk is split into two components: common risk and bank-specific risk, which concerns respectively the common and idiosyncratic variability of bank stock returns. Common risk reflects risks stemming from underlying economic conditions related to the banking industry as a whole, such as changes in the official interest rate, the target exchange rate, or the deposit insurance premia or banking regulations. Bank-specific risk reflects risks unique to particular banks, such as lending to a particular sector of the economy. The chapter estimates the two risk components by a three factor return-generating model[12] using factor analysis. As illustrated in the equation below, the common risk is calculated as the square root of the portion of total return variance that can be explained by the factors. Specific risk is the square root of the difference between total return variance and the square of common risk.

$$\text{Over-all Risk}^2 = \text{Common Risk}^2 + \text{Bank-Specific Risk}^2$$

$$\sigma^2(Risk_i) = \sum_{k=1}^{3} (\beta_i^k)^2 \sigma^2(f^k) + \sigma^2(\varepsilon_i)$$

where each bank have a unique set of βs that measures bank *i*'s exposure to factor *k*. Banks heavily exposed to common risk will have large βs and a high level of systemic risk. The first term, i.e., $\sum_{k=1}^{3} (\beta_i^k)^2 \sigma^2(f^k)$, in the equation is the variability of bank *I*s stock return generated by its exposure to the three systematic factors. The second term above denotes the variability in bank *J*s stock generated by its exposure to bank's concentration in particular industries or regions dominated by ε .

Summary statistics describing the risk variables based on a factor model appears in Table 3.3. Panel (a) presents the average values in each sample year, while panel (b) presents summary statistics of total observations. All risk variables are in the form of percentage change. As the table indicates, over-all riskiness and common riskiness of the sample banks follows a U-shape movement, decreasing and then increasing over the sample period. In contrast, the specific riskiness of banks first increases and then decreases over the sample period and has relatively higher variability than other two risk measures.

[12] The number of factor is determined by the Kaiser-Guttman approach in Eviews 6.0.

3.3.2 Granger Causality Test

3.3.2.1 Applicability of "Panel Causality Test"

The section employs a Granger causality test to assess the interbank market discipline of 12 major UK banks between a number of risk variables and banks' NIP, which have been described earlier. If the riskiness of a bank Granger causes its access to interbank funding (measured by NIP), the market is risk sensitive and is monitoring risk. Given the confirmed risk sensitivity, the increasing NIP of the borrowing banks implies increasing monitoring incentives of the lending banks. If the lending bank's monitoring incentives Granger causes bank's riskiness, it is very likely that the interbank market disciplines banks. However, the original Granger test (1946) was designed to deal with single time series data without cross sections. Furthermore, later studies that extend the Granger test to panel data (see Holtz-Eakin et al., 1988; Hsiao 1989; Weinhold 1996, 1999; Hurling and Venet 2001 and Hurling 2004) fail to provide a satisfactory solution to deal with the power of the test, the key concerns of "panel causality test". The null hypothesis of non-causality is rejected as long as one bank in the panel displays significance in terms of the causality relationship. Also, the rejection of the null hypothesis does not provide any guidance as to the number or the identity of the particular panel members for which the null of non causality is rejected. If a causality relationship between a pair of variables exists, say X Granger causes Y, in one cross section, but not in the rest of the cross-sections in the panel, the question is whether one could thus conclude "X Granger causes Y statistically for the whole panel"; and if not, then how many cross-sections should be tested positive to enable such a conclusion. Moreover, the test statistics used in the panel literature are eventually associated with individual cross sections and therefore do not facilitate a quicker calculation than performing the original Granger causality test in each cross section. The detail of a "panel causality test", illustrated by Hurling's paper, is explained in Appendix 3.1.

3.3.2.2 Granger Causality Test

Due to the limitations of the existing "panel causality test" analyzed above, the chapter performs the original Granger (1946) test on each individual bank in the panel. First, a unit root test is performed on each variable. Since all variables are in the form of percentage change, the null hypothesis of non-stationary is rejected.

For each individual bank i = 1,…,N, the Granger test considers the following linear model at time t = 1,…,T:

$$y_{i,t} = a_i + \sum_{k=1}^{K} r_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t}$$

where in the first step mentioned earlier, y represents a borrowing bank I's access to interbank funding (measured by NIP) while x represents a risk measure of the borrowing bank I described in the previous section; in the second step, y represents a risk measure of borrowing bank I's while x represents the lending bank's monitoring incentives (measured by NIP); k represents the number of lag and is determined by Akaike info criterion (AIC). However, as the direction of causality may depend critically on the number of lagged terms included, it listed test results with different lags following Summers and Heston (1991). The null hypothesis for both steps of test is H_0:$\sum a_i = 0$, that is, x does not Granger causes y. F test is applied to test this hypothesis. To facilitate comparison between banks, P-values of the F-test are plotted.

The results are presented in Figures 3.1 to 3.7, and Tables 3.4 and 3.5. Figures 3.1 to 3.7 plot the P-values of the causality test between risk measures and NIP. In each graph, the black line represents the null hypothesis that NIP, not Granger, causes a risk measure; the grey line represents the null hypothesis that NIP, not Granger, causes overall risk. The dash dots represent the 0.05 significance level. The tests in both directions include a different number of lag terms denoted on the horizontal axis.

As the graphs display, the black lines are generally above the 0.05 significance level, indicating that the majority of banks are insensitive to the risk of the interbank borrowers. However, the few regressions significant in the F-test are presented in Table 3.4. Specifically, the first three columns suggest that Barclays, Charter and RBS's access to interbank funding is reduced when the overall risk increases. The fourth column implies that Lloyds TSB's access to interbank funding is reduced when its asset quality (measured by LLP) deteriorates. The fifth to seventh columns indicate that only Barclays and RBS's access to interbank funding is reduced when their capital (measured by CAR) contracts. However, the signs of LAR coefficients in the next two columns suggest that an increase in the liquidity risk of Northern Rock (NR) and RBS leads to an increase in banks' access to interbank funding. This can be attributed to the function of the interbank market, i.e. providing optimal allocation of resources from banks sufficient in funding to banks lacking funding. Similarly, the signs of Common Risk coefficients in the last column indicate that an increase in common risk of HSBC leads to an increase in banks' access to interbank funding. The latter is probably due to the herding behaviour of some banks such as HSBC. Moreover, the results suggest that no investors are sensitive to the specific riskiness or earning ability of a bank.

In addition, Figures 3.1 to 3.7 show that the grey lines are generally above the 0.05 significance level. This indicates that, even regardless of the monitoring incentives, generally NIP not Granger causes a bank's riskiness. However, the few regressions significant in the F-test are presented in Table 3.5. Compared with the banks in Table 3.4, Table 3.5 suggests that the banks monitored by investors shown in Table 3.4 do not reduce their riskiness accordingly. Hence, Step 2 of the test finds no evidence of interbank market discipline. In particular, the signs of the NIP coefficients imply that an increase in NIP leads to an increase in Lloyds TSB's over-all riskiness, a deterioration in HBOS's asset quality or a decrease in the earning ability of Barclays and HSBC. Among the four banks, Lloyds TSB and Barclays are found in Table 3.4 to be monitored by investors according to their asset quality and capital position respectively, while HBOS and HSBC are unmonitored. Consistent with the reason described above for Table 3.4, it is plausible to find that interbank borrowing increases the liquidity position of two banks. Similar to Table 3.4, Table 3.5 finds positive causality relationship that runs from NIP to HSBC's common risk. This implies that the herding behaviour of HSBC is probably encouraged by its interbank borrowing.

3.3.3 Panel least-squared regression

In the previous section, Granger causality tests were performed on individual banks. This section tests the same hypotheses of market discipline, but on panel data. This is achieved by using panel least-squared regression. In particular, it evaluates whether the coefficient β_2 in the following equation[13] is equal to zero:

$$Risk_{it} = \beta_1 + \beta_2 NIP_{it} + \beta_3 Asset_{it} + \beta_4 (Asset)_{it}^2 + \varepsilon_{it} \tag{3.1}$$

where $Risk_{it}$ denotes a measure of the risk incurred by bank *I* at time *t*; NIP denotes net interbank position of a bank *I* at time *t*. In addition, it adds two new explanatory variables ----logarithm of total asset and its squared term to control for both linear and non-linear size effect on risk undertaking. If the null of β_2=0 is rejected, the test can conclude there is evidence of market discipline.

[13] The fixed effect of the panel LS regression produces no different in the result: insignificance of the coefficient β_2.

However, it is important to note that the estimation of equation (3.1) is regarded as the second step of the test: effectiveness of risk control. The first step of testing risk sensitivity is performed indirectly by testing the endogeneity of NIP in equation (3.1) with regards to the risk variable, $Risk_{it}$. Formally, if NIP is endogenous, there exists a simultaneous equation of (3.2) or (3.5) as below:

$$NIP_{it} = \alpha_1 + \alpha_2 Risk_{it} + \upsilon_{it} \tag{3.2}$$

The section applies Pindyck and Rubinfeld's version of the Hausman endogeneity test which is specified in Appendix 3.2. If NIP is endogenous, the test would proceed to estimate equation (3.1). However, if it is not rejected, the section would conclude that there is no evidence of interbank market discipline. Then, the estimation of equation (3.1) is aimed at investigating the impact of interbank borrowing on bank risk, if the borrowing banks are unmonitored.

Table 3.6 presents the results of the Hausman endogeneity test. In general, the table implies that NIP is not endogenous in a bank's riskiness, because the coefficients of $\hat{\mu}_{it}$ are statistically not different to zero. Intuitively, it suggests that the borrowing banks' access to the interbank funding is generally not influenced by their riskiness. However, there is one exception in the regression of LLP, where the coefficients of $\hat{\mu}_{it}$ are statistically different from zero at a significance level of 10%. This implies that the credit risk (LLP) is weakly endogenous in NIP in equation (3.1).

Estimations of equation (3.1) are presented in Tables 3.7 and 3.8. Table 3.7 contains risk measures using banks' financial accounts, while Table 3.8 contains risk measures using stock market data and factor models. To control for endogeneity in the regression of LLP, a Panel Two-Stage Least Squares regression (2SLS) is estimated, incorporating an instrumental variable (IV) which is correlated with NIP, but uncorrelated with the Risk variable. The chapter uses a cash-to-asset ratio as IV because banks have a stronger incentive to demand interbank financing if their cash ratio is low. For the same reason, the section does not involve LAR, the liquidity position, as one of the risk variables to test market discipline. The results in Table 3.7 show that all of the coefficients of NIP are statistically not different from zero. In particular, the signs of NIP coefficients (highlighted in bold) imply that the change of NIP has no influence on banks' decision to take more credit risk and hold less capital. The coefficient signs are largely consistent with Demirgüç-Kunt and Huizinga (2009), who find banks that heavily rely on non-deposit wholesale funding tend to be more fragile. Moreover, the positive sign of NIP coefficient (i.e. 1.789706) under the regression of LLP implies that α_2 in equation (3.2) is positive; thus, interbank lenders generally do not risk-ration interbank loans. The results in Table 3.8 also show that all of the coefficients of NIP are statistically not different from zero, implying that the change of NIP has no influence on borrowing banks' over-all riskiness, decomposed common riskiness and specific riskiness.

In summary, the panel squared regression test finds little evidence of risk sensitivity: interbank borrowers are generally unmonitored by their lenders. With little lender accountability, our test finds that the variability of interbank exposure has no power to alter the risk taking activities of interbank borrowers.

3.4 UK interbank market: weak risk sensitivity

The empirical results of little risk sensitivity appear to be inconsistent with other empirical studies. As mentioned in the literature review, Dinger and Hagen (2008) discover strong lender accountability in CEE countries and Furfine (2001) and King (2004), among others, find there is evidence of risk pricing or rationing in the US Fed market, though the impact of the latter is marginal.

Nevertheless, it is very likely that the different results originate from the different nature of these markets. In CEE countries, according to Dinger and Hagen (2008), there is a two-tier banking system structure due to banking specialization. Large or incumbent banks, which dominate the deposit markets, are generally net lenders to the interbank market, while the smaller or new entrant banks, which have little access to customer deposits, but a large demand for non-bank loans from small and medium-sized enterprises, are generally net borrowers of the interbank market. Thus, the banking specialization in CEE countries creates a unidirectional fund transfer from first tier large banks to second tier small banks. Dinger and Hagen (2008) also point out that, although the large banks enjoy implicit government deposit guarantees because of repeated recapitalization by the government, the small banks are allowed to fail. For these reasons, lenders of the interbank market in CEE countries have incentives to monitor the riskiness of the borrowers

In contrast, the interbank borrowers in the UK interbank market are generally large institutions. Table 3.9 illustrates the net interbank borrowing position of the 12 major UK banks in the order of bank size (total assets) over the sample period from 1995 to 2007. The interbank position (NIP) is calculated as above, as interbank liabilities minus interbank assets divided by total assets. A positive NIP indicates that the bank is a net interbank borrower in the market, while a negative NIP indicates that the bank is a net provider of interbank funds. As can be seen from the table, larger banks on the lower half of the table are generally net interbank borrowers, while the smaller banks on the upper half of the table are generally net interbank lenders. Moreover, the UK market based in London is highly concentrated: over 70% of total lending between banks operating in the UK is accounted for by only 10 to 15 large institutions (Wells 2004, and Elsinger, Lehar & Summer 2006), compared to 719 in U.S. (Furfine 1999). Therefore, the large banks serve as money centres which usually have systemic importance in the entire banking sector (as explained in Chapter 2). Thus, the disciplining incentives of interbank lenders could be hampered by 'too-big-to-fail' consideration, since the interbank lenders may expect potential bail-out of the large interbank borrowers.

Another factor causing risk insensitivities in the UK interbank market relates to the maturity of interbank loans. As mentioned by Rochet and Tirole (1996), the effectiveness of peer monitoring requires interbank loans to be medium- or long-term loans, so "lenders cannot fly by night and escape their monitoring obligations". In CEE countries, Dinger and Hagen (2008) indicate that the interbank exposures are characterized by long-term maturity. However, as illustrated in Figure 3.8, the majority of interbank assets or liabilities in UK are less than one year and more than 80% of the transactions are less than three months. Therefore, it is plausible that the UK has weaker lender accountability than CEE countries.

3.5 Risk Sensitive, but Ineffective Risk Control: a Theoretical Model

Based on the empirical results and the analysis of the UK interbank market in section 3.3 and section 3.4, this section develops a simple model which demonstrates that lenders' monitoring incentives (proxied by risk pricing on interbank borrowing) could still fail to prevent the borrowing banks from investing in riskier assets. It also demonstrates that the maturity of interbank liabilities or borrowings could be negatively related to the risk taking behaviour of borrowing banks. In order to focus on the relationship between interbank borrowings and lending decisions of banks, the model assumes that banks have no equity and finance all assets of size 1 by interbank borrowing of the same size.

It is assumed that each bank invests a portfolio of assets which may contain non-financial loans, interbank loans, or other financial loans. Dependant on their riskiness, the portfolio assets can be categorized into: "good" assets and "bad" assets. The return of a "good" asset is R_G with the probability of Π_G in case it repays or 0 otherwise; the return of a "bad" asset is R_B with the probability of Π_B in case it repays or 0 otherwise. "Good" assets have a higher net present value than "bad" assets:

$$R_G\Pi_G - 1 > R_B\Pi_B - 1, \Pi_G > \Pi_B$$

However, in order to attract investment, the "bad" assets have a higher return than the "good" assets:

$1 < R_G < R_B$

Depending on the maturity of assets, the portfolio assets can be further categorized into: "good" long-term assets, "good" short-term assets, "bad" long-term assets, and "bad" short-term assets. The share of total short-term assets is Φ, while the share of total long-term assets is $1-\Phi$. However, in order to focus on the banks' behaviour in choosing riskiness, the returns and expected returns of the total "good"/"bad" assets (denoted by R_G, R_B, $R_G\Pi_G$ and $R_B\Pi_B$) are not affected by Φ.

Lenders of interbank transactions have the incentives and the technology to screen the assets owned by the borrowing banks. When pricing the portfolio loan of size 1, they charge more for the proportion of "bad" assets than the proportion of "good" assets, and require a total repayment of:

$\delta d_G + (1-\delta) d_B$

$1 < d_G < d_B$, $0 \leq \delta \leq 1$

where d_G denotes the repayment required for the share lending to "good" assets, d_B denotes the repayment required for the share lending to "bad" assets and δ denotes the share of assets screened as "good"[14]. Therefore, if δ, i.e. the share of the "good" assets, is high/low, a borrower is charged less/more repayment. In addition, the net expected return of "good" assets in a case whereby the borrowing banks repay is higher than that of "bad" assets:

$$(R_G - d_G)\Pi_G > (R_B - d_B)\Pi_B$$

However, the net return of "good" assets is lower than that of "bad" assets, so that banks are still attracted to invest in "bad" assets:

$$R_B - d_B > R_G - d_G > 0,$$

For sake of simplicity, it is assumed that the banks' assets and liabilities have the same maturity structure. Therefore, Φ represents the share of long-term borrowings and 1- Φ represents the share of short-term borrowing. The term structure of the interbank borrowing rate is $1 < d_s < d_l$, where d_s denotes a short-term return rate and d_l denotes a long-term return rate, which are independent of each other. If denoting the repayment for financing long-term and short-term "good" assets respectively as d_{GL} and d_{GS}, and denoting the repayment for financing long-term and short-term "bad" assets respectively as d_{BL} and d_{BS}, d_G and d_G can be expressed as:

[14] As the lenders have the technology to screen the assets of borrowing banks, their assessment in the asset profile of borrowing banks is correct.

$d_G = \Phi d_{GL} + (1\text{-}\Phi)\ d_{GS} = \Phi(d_{GL} - d_{GS}) + d_{GS}$

$d_B = \Phi d_{BL} + (1\text{-}\Phi)\ d_{BS} = \Phi(d_{BL} - d_{BS}) + d_{BS}$

where $d_{BL} > d_{BS} > 1$, $d_{GL} > d_{GS} > 1$ as long-term loans are required for higher repayment than short-term loans.

There is only one time period of concern. This is when the borrowing banks decide the investment portfolio given interbank funding. The investment decision made by banks depends on whether banks' net expected return (NER) will be maximized. The interbank funding is provided on the basis that the net expected return (NER) from the portfolio investment by the borrowing banks is greater than 0.

Proposition 1: Interbank borrowing banks tend to choose a lower δ, i.e. a higher share of "bad" assets to maximize their net expected return (NER) if the "bad" assets are much riskier than the "good" assets and the probability that both "bad" assets and "good" assets will repay is very small:

$\Pi_G - \Pi_B > \Pi_G \Pi_B$

Proof: See Appendix 3.3.

***Proposition 2**:* Banks can always increase their NER by increasing their share of short-term interbank borrowing. If $\Pi_G - \Pi_B > \Pi_G \Pi_B$, there is a positive relationship between the share of short-term interbank borrowing and the tendency of borrowing banks to take more risk when they try to maximize their net expected return.

Proof: See Appendix 3.3

3.6 Conclusion

This chapter finds that previous literature on market discipline either focuses on testing the risk sensitivity of investors or testing the unidirectional causality that runs from interbank borrowings to bank's riskiness. The chapter contends that either way of testing is not robust to verify the effective risk control by the interbank market. However, the chapter argues that the hypothesis can be verified by a combination of the two methods applied in two steps.

The chapter tests empirically interbank market discipline in the UK. The empirical results give little support to interbank market discipline in the UK. Firstly, it finds that the market investors show weak risk sensitivity. Only a small proportion of banks monitor risk when extending their loans. Secondly, it finds that banks that are monitored do not reduce their risk accordingly. Thirdly, and more justifiably, it is found that some unmonitored banks take higher risks when they obtain more interbank funding.

The results of weak risk sensibility are analyzed, based on the nature of the UK interbank market. Firstly, since the UK interbank market consists of a few large institutions, the peer monitoring incentives could be dampened because of a "too-large-to-fail" assumption. Secondly, as the majority of UK interbank transactions have a term of less than three months, the length of time to maturity is too short to satisfy the lender accountability required by the theory of market discipline. Lenders can easily fly to escape their monitoring obligations.

Moreover, the chapter explains the scenario of "ineffectiveness risk control, though monitored" in a simple theoretical model. The model demonstrates that banks that have their risk priced by their lenders could still choose a riskier asset portfolio to maximize their net expected return. This happens if the "bad" assets are much riskier than the "good" assets and the probability that both "bad" assets and "good" assets will repay is very small.

Table 3.1: Comparison of variables in the SEER rating system and in this chapter

	Variables in SEER rating system	*Effect on bank credit-worthiness*	*Variables in this chapter*	*Effect on bank credit-worthiness*
Asset Quality	Loans 30-90 days past due Loans past due 90+ days Nonaccrual loans Other real estate owned Commercial & industrial loans Residential real estate loans	- - - - - +	Loan loss provision to gross loan (LLP)	-
Capital	Tangible net worth (CAR)	+	Capital to asset ratio (CAR)	+
Earnings	Net income (ROA)	+	Net income to asset ratio (ROA)	+
Liquidity	Investment securities Large time deposits	+ -	Cash to asset ratio (LAR)	+

Table 3.2: Summary statistics of the risk variable based on SEER

	(a) Average over 1996-2007			
	LLP	CAR	ROA	LAR
1996	102.88	9.15	31.60	28.62
1997	9.23	-3.04	-3.19	-20.90
1998	64.92	1.16	5.88	-1.76
1999	-4.56	1.22	2.41	49.76
2000	-35.60	3.53	8.34	-35.73
2001	27.89	-0.84	-16.60	33.33
2002	-75.78	-6.07	-13.97	217.09
2003	3.87	-1.77	-40.39	-3.39
2004	-38.97	-0.76	-22.72	30.90
2005	-190.99	-13.55	51.86	28.06
2006	71.26	0.01	10.12	106.18
2007	79.84	-7.72	-13.51	5.43
	(b) Summary statistics			
Mean	-29.46	-4.67	5.84	38.18
Median	1.29	-4.91	-0.66	4.93
Maximum	763.06	24.69	355.28	1031.19
Minimum	-1589.92	-51.51	-83.53	-97.30
Std. Dev.	252.72	13.12	66.40	149.77

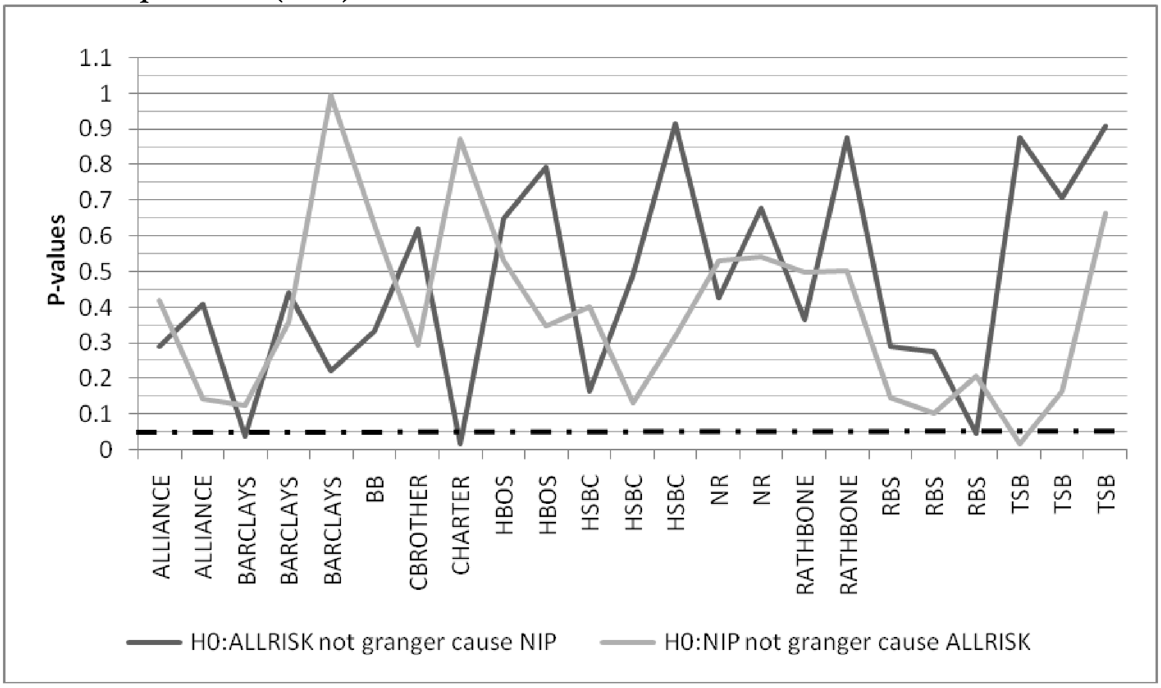
Source: Author's calculations, based on data from the banks' annual reports.

Table 3.3: Summary statistics of the risk variable based on factor models

	(a) Average over 2002-2007		
	Overall Risk	Common Risk	Specific Risk
2002	14.01	55.07	-20.10
2003	-17.74	-9.41	-10.11
2004	-42.53	-56.06	10.01
2005	5.09	67.91	18.84
2006	15.52	18.32	96.82
2007	17.66	59.99	-39.37
	(b) Summary Statistics		
Mean	-2.36	23.84	12.06
Median	-1.24	-0.60	-24.35
Maximum	61.17	331.21	508.23
Minimum	-58.96	-87.45	-100.00
Std. Dev.	27.29	83.29	117.01

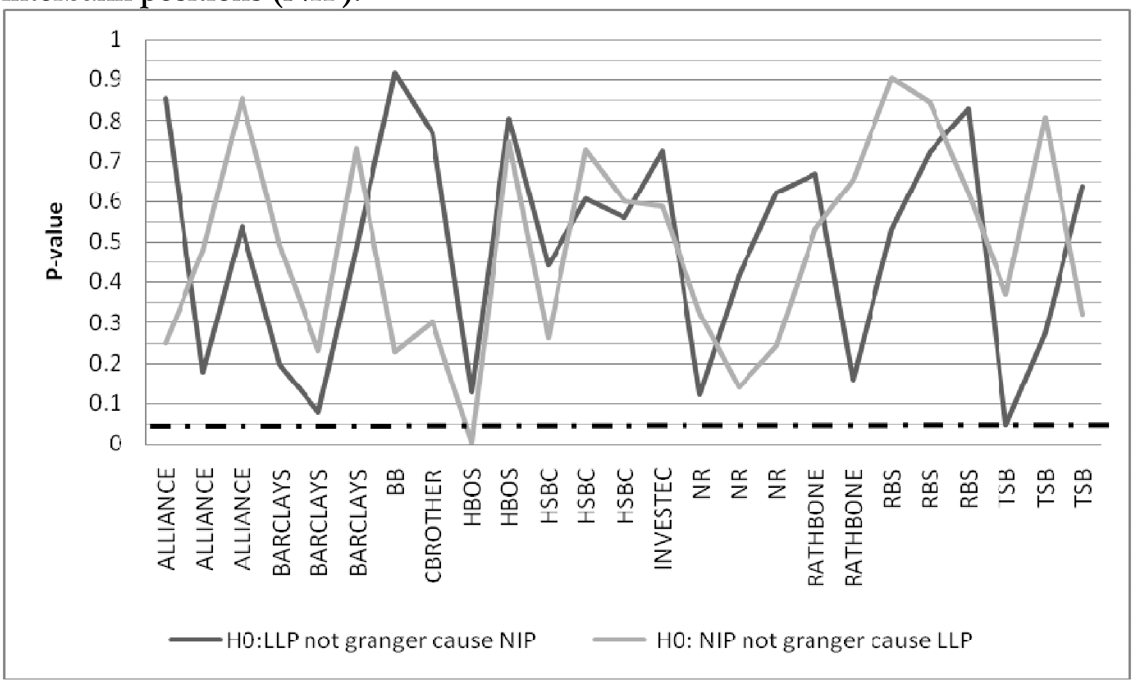
Source: Author's calculations, based on banks' stock price from Thomson DataStream.

Figure 3.1: P-values of the Granger causality test between overall risk and net interbank positions (NIP)



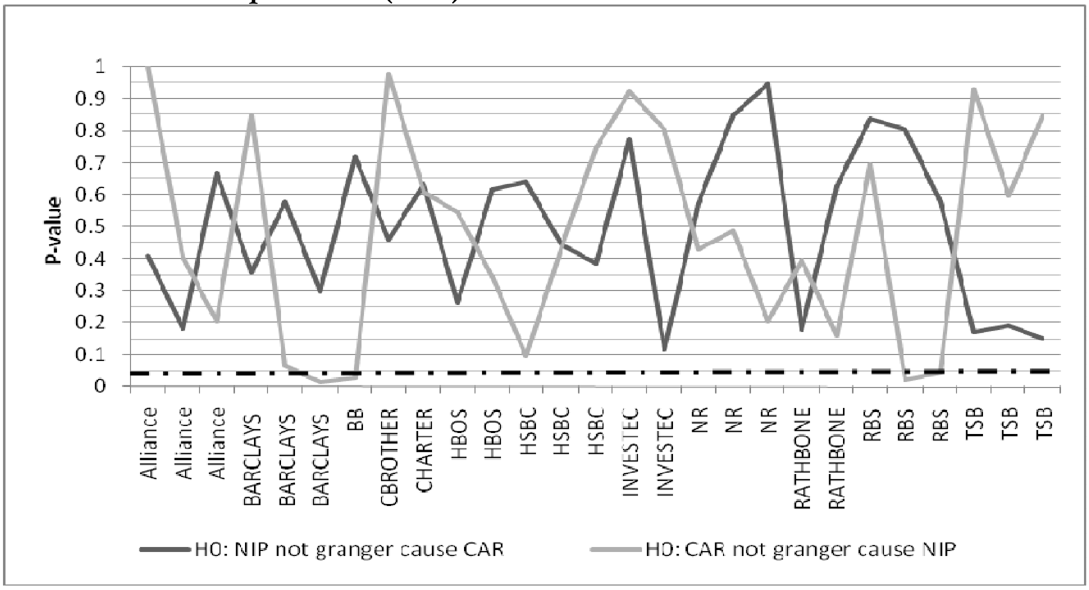
Note: Horizontal axis represents number of lags (up to 3 due to limited observations) for different banks.

Figure 3.2: P-values of the Granger causality test between credit risk (LLP) and net interbank positions (NIP).



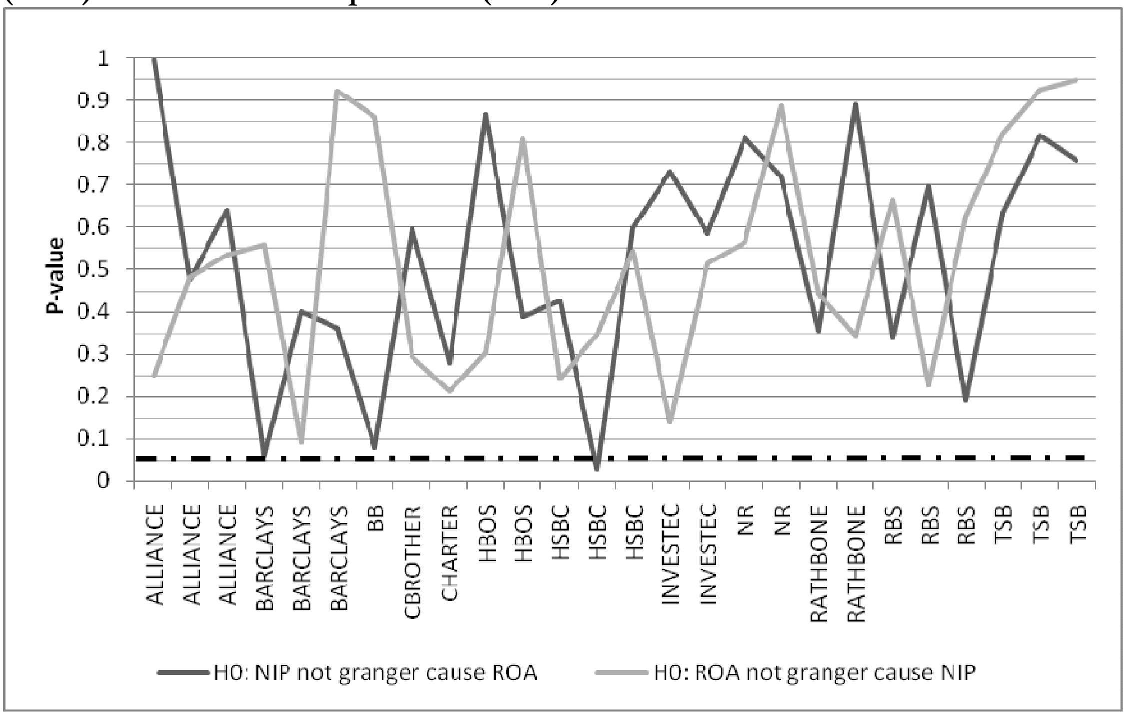
Note: Horizontal axis represents number of lags (up to 3 due to limited observations) for different banks

Figure 3.3: P-values of the Granger causality test between capital to asset ratio (CAR) and net interbank positions (NIP).



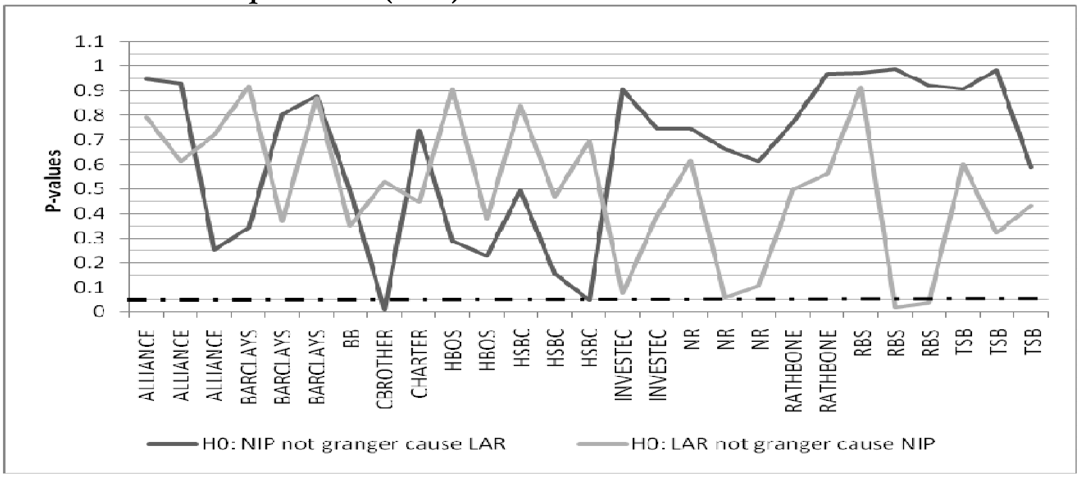
Note: Horizontal axis represents number of lags (up to 3 due to limited observations) for different banks

Figure 3.4: P-values of the Granger causality test between net income to asset ratio (ROA) and net interbank positions (NIP).



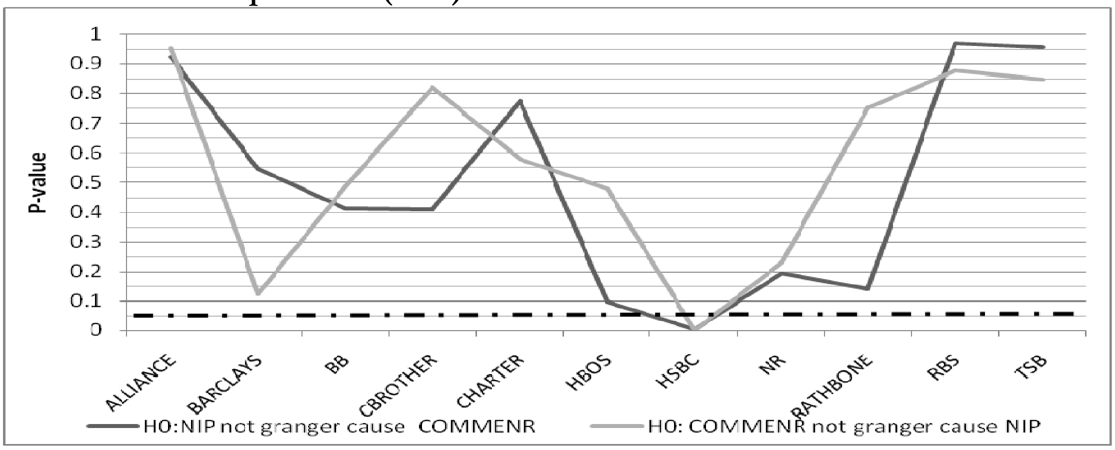
Note: Horizontal axis represents the number of lags (up to 3 due to limited observations) for different banks.

Figure 3.5: P-values of the Granger causality test between cash to asset ratio (LAR) and net interbank positions (NIP).



Note: Horizontal axis represents number of lags in order (up to 3 due to limited observations) for different banks.

Figure 3.6: P-values of the Granger causality test between common risk (COMMR) and net interbank positions (NIP).



Note: Horizontal axis represents number of lags in order (up to 3 due to limited observations) for different banks.

Figure 3.7: P-values of the Granger causality test between specific risk (SPECR) and net interbank positions (NIP).

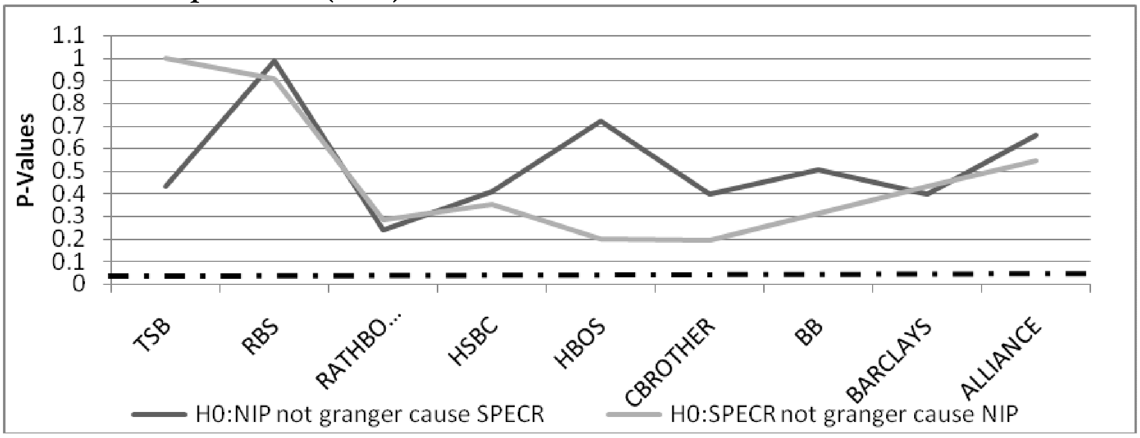


Table 3.4: Results that are significant at 5% level in the Granger Causality test (H_0: Risk variable not Granger causes NIP)

	Dependent variable: NIP									
	Barclays	Charter	RBS	TSB	Barclays	BB	RBS	NR	RBS	HSBC
Intercept	-5.718178 (24.92130)	-88.99574** (25.54543)	420.8679 (104.4713)*	216.3565 (207.8174)	15.53129 (22.04540)	-114.1248** (24.09293)	168.3536 (161.6984)	407.6413 (216.2108)	-1565.512 (299.2102)	20.94051*** (1.210703)
NIP_{t-1}	0.015104 (0.069695)	0.338419 (0.209732)	0.640598* (0.185820)	-0.063728 (0.282189)	0.124482 (0.236053)	-0.778200* (0.186555)	-0.148717 (0.221680)	0.018332 (0.254450)	-0.721100 (0.279974)	1.058043*** (0.055380)
NIP_{t-2}	-	-	-1.231944** (0.208778)	-	-0.261086** (0.073266)	-	0.151723 (0.221786)	-0.111457 (0.248659)	0.493930* (0.130134)	-
NIP_{t-3}	-	-	-0.963048*** (0.200156)	-	-	-	-	-	0.568144* (0.159084)	-
All $risk_{t-1}$	-1.806042** (0.729505)	-3.057607** (0.617901)	-52.49717** (6.685440)	-	-	-	-	-	-	-
All $risk_{t-2}$	-	-	19.55055* (6.685440)	-	-	-	-	-	-	-
All $risk_{t-3}$	-	-	-8.040832 (5.832848)	-	-	-	-	-	-	-
LLP_{t-1}	-	-	-	-15.61628** (6.662353)	-	-	-	-	-	-
CAR_{t-1}	-	-	-	-	-1.768305 (2.029733)	-12.45937** (2.116911)	-13.33960 (7.482159)	-	-	-
CAR_{t-2}	-	-	-	-	4.177723** (1.593111)	-	31.00312*** (7.332132)	-	-	-
LAR_{t-1}	-	-	-	-	-	-	-	-3.374231** (0.995636)	-27.80436* (7.303013)	-
LAR_{t-2}	-	-	-	-	-	-	-	12.65568** (3.742660)	-81.76056** (9.119915)	-
LAR_{t-3}	-	-	-	-	-	-	-	-	-59.73589* (19.79436)	-
$Commr_{t-1}$	-	-	-	-	-	-	-	-	-	0.584774*** (0.023598)
R^2	0.446149	0.895760	0.971225	0.474010	0.772955	0.952118	0.794266	0.773953	0.773953	0.996770

Note: one, two and three asterisks represent significance at 10%, 5% and 1% respectively. The choice of the number of lag to be presented for each bank depends on the Akaike info criterion (AIC).

Table 3.5: Results that are significant at 5% level in the Granger Causality test (H_0: NIP not Granger causes risk variable)

	Overall	*LLP*	*ROA*		*LAR*		*Common*
	TSB	HBOS	Barclays	HSBC	Cbrother	HSBC	HSBC
NIP_{t-1}	0.032310** (0.010184)	0.040311*** (0.008152)	-0.036246* (0.016675)	-0.057784 (0.268943)	0.027322*** (0.002216)	0.789320 (0.295909)	2.981134*** (0.146290)
NIP_{t-2}	-	-	-	-0.696620** (0.175542)	-	0.417337 (0.522408)	-
NIP_{t-3}	-	-	-	-	-	0.945272** (0.193969)	-
$All\ risk_{t-1}$	0.069723 (0.233493)	-	-	-	-	-	-
$All\ risk_{t-2}$	-	-	-	-	-	-	-
$All\ risk_{t-3}$	-	-	-	-	-	-	-
LLP_{t-1}	-	-0.052650 (0.181383)	-	-	-	-	-
ROA_{t-1}	-	-	-0.380271 (0.227822)	-0.031939 (0.196383)	-	-	-
ROA_{t-2}	-	-	-	-0.498221** (0.154171)	-	-	-
LAR_{t-1}	-	-	-	-	-1.120551*** (0.048149)	-0.684479 (0.235329)	-
LAR_{t-2}	-	-	-	-	-	-0.502586 (0.264155)	-
LAR_{t-3}	-	-	-	-	-	-0.094709 (0.184784)	-
$Commr_{t-1}$	-	-	-	-	-	-	-1.079635*** (0.062336)
Intercept	-11.96051 (7.935682)	8.224334** (2.785264)	-0.830326 (5.642223)	-13.18699 (4.557201)	14.59188*** (0.645218)	32.31959* (8.840561)	-7.491344 (3.198158)
R^2	0.593632	0.895760	0.577135	0.880224	0.996390	0.984604	0.999218

Note: one, two and three asterisks represent significance at 10%, 5% and 1% respectively. The choice of the number of lags to be presented for each bank depends on the Akaike info criterion (AIC).

Table 3.6: Hausman endogeneity test (H_0: NIP is not endogenous in a risk measure.)

	Risk variables				
	All risk	*LLP*	*CAR*	*ROA*	*LAR*
NIP	-0.046490	-0.164522*	-0.003897	-0.058887	0.083218
	(0.044232)	(0.079646)	(0.011237)	(0.042787)	(0.080109)
$\hat{\mu}_{it}$	0.054863	0.173418*	0.000577	0.059764	0.024916
	(0.047036)	(0.084696)	(0.011949)	(0.045500)	(0.085188)
Intercept	16.70794	45.42667*	-0.770837	11.52210	22.05103
	(11.53145)	(20.76422)	(2.929525)	(11.15478)	(20.88487)
R-squared	0.132834	0.326463	0.080485	0.174111	0.625095

Note: one, two and three asterisks represent significance at 10%, 5% and 1% respectively. $\hat{\mu}_{it}$ represents the residual in the regression of $NIP_{it} = \gamma_1 + \gamma_2 Asset_{it} + \gamma_3 Asset_{it}^2 + \mu_{it}$.

Table 3.7: Relationship between interbank position and bank risk (financial accounts data)

Regressors \ Risk variables	*LLP*	*CAR*	*ROA*
NIP	**1.789706**	**-0.000184**	**0.000463**
	(14.85381)	(0.000759)	(0.003936)
Assets	-527.6338	-1.959371	18.90870*
	(4431.193)	(2.164157)	(11.37268)
Assets^2	32.02443	0.107070	-0.803481
	(269.2344)	(0.121251)	(0.637544)
Intercept	1186.774	5.029995	-106.8223
	(10007.31)	(9.343376)	(48.56662)
R-squared	-671.843767	0.008208	0.049434
No. of Banks	12	12	11
Total panel Obs.	117	117	105
Sample	1996-2007	1996-2007	1996-2007

Note: One, two and three asterisks represent significance at 10%, 5% and 1% level respectively. To control for endogeneity tested above, an instrumental variable of cash ratio is applied in the regression with the dependent variable of LLP.

Table 3.8: Relationship between interbank position and bank risk (stock market data)

No. of Banks: 10	*Sample period*: 2001-2007	*Total panel Obs:* 70	
	Overall Risk	*Common Risk*	*Specific Risk*
NIP	**-0.000178**	**-0.000217**	**3.85E-05**
	(0.000495)	(0.000444)	(0.000123)
Assets	-2.30E-09***	-2.10E-09***	-1.95E-10
	(6.01E-10)	(5.40E-10)	(1.50E-10)
Assets^2	2.92E-16***	2.97E-16***	-5.01E-18
	(9.72E-17)	(8.73E-17)	(2.43E-17)
Intercept	0.002553***	0.002108***	0.000445***
	(0.000337)	(0.000302)	(8.41E-05)
R^2	0.281132	0.305810	0.378425

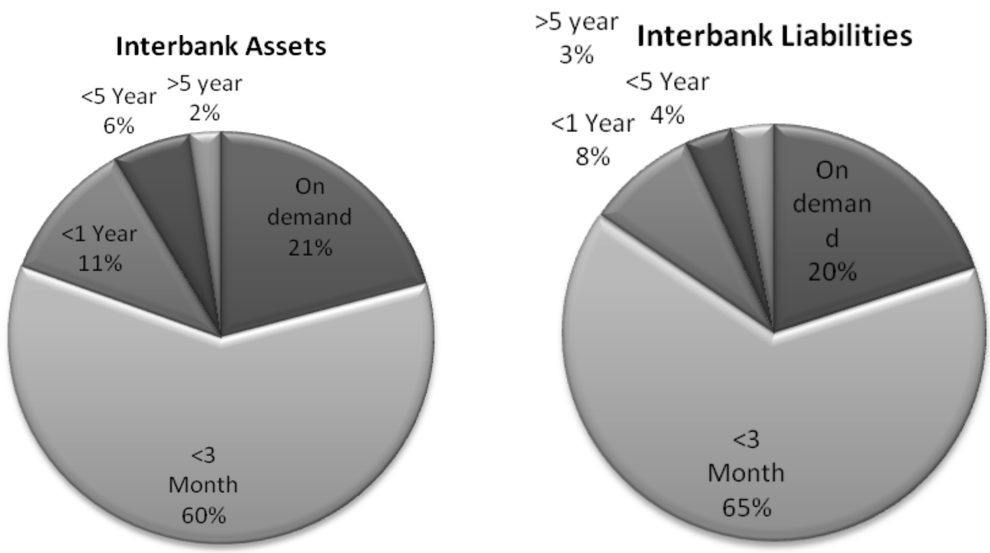
Note: One, two and three asterisks means significance at 10%, 5% and 1% level respectively.

Table 3.9: Average net interbank borrowing positions (NIP) of major UK banks from 1995-2007

Bank	Interbank borrowing position	Total assets (£ millions)
INVESTEC	2.82%	17.63938
RATHBONE	-11.65%	714.8471
CBROTHER	-2.04%	4000.162
BB	-4.02%	36396.57
ALLIANCE	3.01%	55103.89
NR	-0.30%	61683.66
CHARTER	-2.39%	185440.9
TSB	1.97%	289586.3
HBOS	5.07%	473899.1
BARCLAYS	5.70%	696219.1
RBS	3.96%	766790.3
HSBC	-5.30%	1355095

Source: Banks' annual reports.

Figure 8: Major UK-resident banks' interbank loans in various maturities as a share of total amount



Source: Annual reports of 15 UK resident banks in 2004

Appendix 3.1: Hurling Panel Causality Test

In traditional panel causality literature before Hurling (2004), econometricians focus on testing the homogeneity of the coefficients on the explanatory variables (see Holtz-Eakin et al. 1985; Hsiao 1989; Weinhold 1996, 1999; Hurling and Venet 2001). In Hurling and Venet (2001), for example, it goes through a three stage procedure to test two stationary variables, denoted *x* and *y*, observed on T periods and on N individuals. In particular, he considers the following linear model for each individual $i = 1,\ldots,N$, at time $t = 1,\ldots,T$:

$$y_{i,t} = a_i + \sum_{k=1}^{K} r_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t}$$

with $K \in N^* \ and\ \beta_i = \left(\beta_i^{(1)},\ldots,\beta_i^{(K)}\right)'$.[15] In Stage 1, it tests homogeneity:

$$H_0 : \beta_i^{(k)} = \beta_j^{(k)} \quad \forall k = 1,\ldots,K$$
$$H_1 : \beta_i^{(k)} \neq \beta_j^{(k)} \quad \forall k = 1,\ldots,K$$

If H_0 is not rejected, implying homogenous coefficients, he then proceeds to stage 2; if H_0 is rejected, he then skips to stage 3. In Stage 2, it tests the null hypothesis of non-causality:

$$H_0 : \beta_i^{(k)} = 0 \quad \forall k = 1,\ldots,K$$
$$H_1 : \beta_i^{(k)} \neq 0 \quad \forall k = 1,\ldots,K$$

If H_0 is not rejected, the test ends and concludes *x* not Granger causes *y*, or termed by Hurling (2001) as Homogeneous Non-Causality (HNC); if H_0 is rejected, the test ends and concludes *x* Granger cause *y*, or Homogeneous Causality (HC). In stage 3, the hypothesis is:

15 For simplicity, individual effects a_i are supposed to be fixed and it assumed that lag orders *K* are identical for all cross-section units of the panel.

$$
\begin{aligned}
H_0 &: \beta_i^{(k)} = 0 \quad \forall i = 1,\ldots,N \\
H_1 &: \beta_i^{(k)} = 0 \quad \forall i = 1,\ldots,N_1 \\
&\quad \beta_i^{(k)} \neq 0 \quad \forall i = N_1+1, N_1+2,\ldots,N
\end{aligned}
$$

where N1 is unknown, but satisfies condition $0 \leq N_1 / N < 1$. If H0 is not rejected, the test ends and concludes *x* not Granger cause *y*, or Homogeneous Non-Causality (HNC); if H0 is rejected, the test ends and concludes *x* not Granger cause *y*, or Homogeneous Non-Causality (HNC); if H0 is rejected, the test ends and concludes *x* Granger cause *y*, or Heterogeneous Causality (HEC). However, the homogeneity test is unnecessary. In Hurling (2008), only one stage of test, i.e. Stage 3 above, is performed.

The major disadvantages of Hurling's papers are:

1. Hurling does not explain much about what it really means for HEC.

Hurling (2007) admit that the rejection of the null of Homogeneous Non Causality does not provide any guidance as to the number or the identity of the particular panel members for which the null of non causality is rejected. Simply speaking, if H_0 is rejected, and X granger causes Y for only one cross section but not for all other cross-sections in the panel, whether one could conclude "X granger causes Y statistically in the whole panel". If not, how large the number of N-N_1 in H_1 above should be to enable to conclude "X granger causes Y".

2. Little improvement on Granger (1969).

Hurling (2004) does not involve any particular panel estimation. The test statistics used in Hurling are in the form of:

$$W_{N,T}^{Hnc} = \frac{1}{N}\sum_{i=1}^{N} W_{i,T}$$

where $W_{i,T}$ denotes the individual Wald statistics for the i^{th} cross-section associated to the individual test H_0: $\beta_i = 0$. As individual test has to be conducted anyway, there is no reason for not to simply perform individual Granger (1969) test.

Appendix 3.2: the Hausman Endogeneity Test

The underlying idea of the Hausman test is to compare two sets of estimates, one of which is consistent under both the null and the alternative and another which is consistent only under the null hypothesis. A large difference between the two sets of estimates is taken as evidence in favour of the alternative hypothesis. Here, the Pindyck and Rubinfeld version of the Hausman test is specified:

$$Risk_{it} = \beta_1 + \beta_2 NIP_{it} + \beta_3 Asset_{it} + \beta_4 Asset_{it}^2 + \varepsilon_{it} \tag{1}$$

$$NIP_{it} = \alpha_1 + \alpha_2 Risk_{it} + \upsilon_{it} \tag{2}$$

Step1: Estimate the equation (3) below

$$NIP_{it} = \gamma_1 + \gamma_2 Asset_{it} + \gamma_3 Asset_{it}^2 + \mu_{it} \tag{3}$$

and retrieve the residual $\hat{\mu}_{it}$

Step2: Estimate the equation (4) below

$$Risk_{it} = \varpi_1 + \varpi_2 NIP_{it} + \varpi_3 \hat{\mu}_{it} + \sigma_{it} \tag{4}$$

and perform a t test on the coefficient of $\hat{\mu}_{it}$, i.e. $\hat{\varpi}_3$.

$H_0 : \varpi_3 = 0$ Consistant estimators of eq(1), NIP is exogenous

$H_1 : \varpi_3 \neq 0$ Inconsistant estimators of eq(1), NIP is endogenous

Appendix 3.3: Proof of Propositions

Proof of Proposition 1:

The investment decision made by banks depends on whether they consider that the transaction will maximize banks' net expected return (NER). However, banks' investment contains a portfolio of both "good" assets and "bad" assets, as illustrated in the table below. Banks' NER must be calculated separately under the four scenarios.

Table 3.10: Probability of repayment and default

Good \ **Bad**	**Repay** Probability: Π_B	**Default** Probability: 1- Π_B
Repay Probability Π_G	***1.*** All (both "good" and "bad") assets repay. Probability: $\boldsymbol{\Pi_G \Pi_B}$	***2.*** "good" assets repay and "bad" assets default. Probability: $\boldsymbol{\Pi_G (1\text{-}\Pi_B)}$
Default Probability 1- Π_G	***3.*** "Bad" assets repay and "good" assets default. Probability: $\boldsymbol{(1\text{-}\Pi_G)\Pi_B}$	***4.*** All assets default. Probability: $\boldsymbol{(1\text{-}\Pi_G)(1\text{-}\Pi_B)}$

1. All (both "good" and "bad") assets repay. Probability: $\Pi_G \Pi_B$

$$NER_{S1} = [\delta(R_G - d_G) + (1-\delta)(R_B - d_B)]\Pi_G \Pi_B$$

2. "Good" assets repay and "bad" assets default. Probability: Π_G $(1\text{-}\Pi_B)$

$$NER_{S2} = [\delta(R_G - d_G) + (1-\delta)(0 - d_B)]\Pi_G (1 - \Pi_B)$$

3. "Bad" assets repay and "good" assets default. Probability: $(1\text{-}\Pi_G)\Pi_B$

$$NER_{S3} = [\delta(0 - d_G) + (1-\delta)(R_B - d_B)](1 - \Pi_G)\Pi_B$$

4. All assets default. Probability: $(1\text{-}\Pi_G)(1\text{-}\Pi_B)$

$$NER_{S4} = [\delta(0 - d_G) + (1-\delta)(0 - d_B)](1 - \Pi_G)(1 - \Pi_B)$$

Since the NER has to be greater than 0, in scenario 4 where the NER is less than 0, banks will not be able to obtain the interbank loans. For other scenarios:

(1) Under the scenario that all assets repay, a bank will be able to obtain the interbank loans if:

$$\left[\delta(R_G - d_G) + (1-\delta)(R_B - d_B)\right]\Pi_G \Pi_B > 0$$
$$\Rightarrow \delta > \frac{R_B - d_B}{(R_B - d_B) - (R_G - d_G)} > 1$$

However, this is impossible because $0 \leq \delta \leq 1$.

(2) Under the scenario that "good" assets repay and "bad" assets default, a bank will be able to obtain the interbank loans if:

$$\left[\delta(R_G - d_G + d_B) - d_B\right]\Pi_G (1 - \Pi_B) > 1$$
$$\Rightarrow \delta > \frac{d_B}{R_G - d_G + d_B}$$

(3) Under the scenario that "bad" assets repay and "good" assets default, a bank will be able to obtain the interbank loans if:

$$\left[-\delta(R_B - d_B + d_G) + (R_B - d_B)\right](1 - \Pi_G)\Pi_B > 0$$
$$\Rightarrow \delta < \frac{R_B - d_B}{R_B - d_B + d_G}$$

It can be proved that $\frac{R_B - d_B}{R_B - d_B + d_G} > \frac{d_B}{R_G - d_G + d_B}$ as below:

$$\frac{R_B - d_B}{R_B - d_B + d_G} - \frac{d_B}{R_G - d_G + d_B} = \frac{(R_G - d_G)R_B - R_G d_B}{(R_B - d_B + d_G)(R_G - d_G + d_B)}$$

which is always negative, since the denominator is greater than zero because R_B -d_B >R_G - d_G>0 and 1<d_G < d_B , while the numerator is always less than zero because (R_G - d_G)R_B < *1*, R_B d_B > *1*.

Therefore, we have to study the following two cases for δ:

(A) $\frac{d_B}{R_G - d_G + d_B} < \delta \leq 1$

In this case, a bank will be able to obtain an interbank deposit if only the "good" assets repay. The first derivative of NER is:

$$\frac{\partial NER}{\partial \delta} = (R_G - d_G) + d_B > 0$$

Therefore, NER is increasing in δ. The local maximum for the interval $(\frac{d_B}{R_G - d_G + d_B}, 1]$ is at 1:

$$NER_{local\ \max}(\delta = 1) = (R_G - d_G)\Pi_G(1 - \Pi_B)$$

(B) $0 \leq \delta < \frac{R_B - d_B}{R_B - d_B + d_G}$

In this case, a bank will be able to obtain an interbank deposit if only the "bad" assets repay. The first derivative of NER is:

$$\frac{\partial NER}{\partial \delta} = -[(R_B - d_B) + d_G] < 0$$

Therefore, NER has a negative relationship with and is decreasing in δ. The local maximum for the interval $[0, \frac{R_B - d_B}{R_B - d_B + d_G})$ is at 0:

$$NER_{local\max}(\delta = 0) = (R_B - d_B)\Pi_B(1 - \Pi_G)$$

Comparing the local maximum at the two cases gives:

$$\begin{aligned}
&(R_B - d_B)\Pi_B(1 - \Pi_G) - (R_G - d_G)\Pi_G(1 - \Pi_B) \\
&= [(R_B - d_B) - (R_G - d_G)][\Pi_G\Pi_B - (\Pi_G - \Pi_B)]
\end{aligned}$$

Since R_B -d_B >R_G - d_G>0, the first term of the multiplication is greater than zero. The comparison depends on the second term.

If $\Pi_G - \Pi_B < \Pi_G\Pi_B$, i.e. the difference in the riskiness between "good" assets and "bad" assets is not larger than the probability that both assets will repay, then banks will choose δ=1, i.e. invest all in "good" assets to maximize their net expected return.

However, if $\Pi_G - \Pi_B > \Pi_G\Pi_B$, i.e. the difference in the riskiness between "good" assets and "bad" assets is larger than the probability that both assets will repay, then banks will choose δ=0, i.e. invest all in "bad" assets to maximize their net expected return.

Above all, under the monitoring mechanism through pricing, borrowing banks still tend to choose a lower δ, i.e. a higher share of "bad" assets to maximize their net expected return (NER) if the "bad" assets are much riskier than the "good" assets and the probability that both "bad" assets and "good" assets will repay is very small:

$$\Pi_G - \Pi_B > \Pi_G \, \Pi_B$$

Specifically, they will choose a δ in the interval $[0, \frac{R_B - d_B}{R_B - d_B + d_G})$ relative to a δ in the interval $(\frac{d_B}{R_G - d_G + d_B}, 1]$, where $\frac{R_B - d_B}{R_B - d_B + d_G} < \frac{d_B}{R_G - d_G + d_B}$.

Proof of Proposition 2:

The relationship between the maturity of interbank loans and the risk taking behaviour of borrowing banks can be studied by inserting the following expression into the NER expressions in proposition 1 above.

$$d_G = \Phi d_{GL} + (1-\Phi)\, d_{GS} = \Phi(d_{GL} - d_{GS}) + d_{GS}$$

$$d_B = \Phi d_{BL} + (1-\Phi)\, d_{BS} = \Phi(d_{BL} - d_{BS}) + d_{BS}$$

As shown in the proof of Proposition 1, banks will successfully obtain interbank loans in two scenarios; thus, it is only necessary to analyze NER_{S2} and NER_{S3} as below:

(1) $\frac{d_B}{R_G - d_G + d_B} < \delta \leq 1$, only "good" assets repay:

$$\begin{aligned} NER_{S2} &= [\delta(R_G - d_G) + (1-\delta)(0 - d_B)]\Pi_G(1-\Pi_B) \\ &= \Pi_G(1-\Pi_B)\{\delta\{R_G + \phi[(d_{BL} - d_{BS}) - (d_{GL} - d_{GS})] + d_{BS} - d_{GS}\} \\ &\quad - \phi(d_{BL} - d_{BS}) - d_{BS}\} \end{aligned}$$

The first derivative is:

$$\frac{\partial NER_{S2}}{\partial \phi} = (\delta - 1)(d_{BL} - d_{BS}) - \delta(d_{GL} - d_{GS})$$

which is always negative since δ-1<0, $d_{BL}>d_{BS}$, $\delta>0$ and $d_{GL}>d_{GS}$. Hence, *NER* is decreasing in Φ and banks will reduce the share of long-term interbank loans to maximize the *NER*. As δ has a positive relationship with *NER* for the interval $(\frac{d_B}{R_G - d_G + d_B}, 1]$, it implies that Φ has a negative relationship with δ in maximizing NER. This means borrowing banks will maximize NER by decreasing the share of long-term interbank loans and increasing the share of "good" assets.

(2) $0 \le \delta < \frac{R_B - d_B}{R_B - d_B + d_G}$, only "bad" assets repay:

$$
\begin{aligned}
NER_{S3} &= [\delta(0 - d_G) + (1-\delta)(R_B - d_B)](1-\Pi_G)\Pi_B \\
&= (1-\Pi_G)\Pi_B\{-\delta\{R_B + \phi[(d_{GL} - d_{GS}) - (d_{BL} - d_{BS})] + d_{GS} - d_{BS}\} \\
&\quad + R_B - \phi(d_{BL} - d_{BS}) - d_{BS}\}
\end{aligned}
$$

The first derivative is:

$$\frac{\partial NER_{S3}}{\partial \phi} = (\delta - 1)(d_{BL} - d_{BS}) - \delta(d_{GL} - d_{GS})$$

which is always negative since δ-1<1, $d_{BL}>d_{BS}$, δ>0 and $d_{GL}>d_{GS}$. Hence, *NER* is decreasing in Φ and banks will reduce the share of long-term interbank loans to maximize the NER. As δ has a negative relationship with *NER* for the interval $[0, \frac{R_B - d_B}{R_B - d_B + d_G})$, it implies that Φ has a positive relationship with δ in maximizing NER. This means borrowing banks will maximize NER by decreasing the share of long-term interbank loans and reducing the share of "good" assets.

Overall, banks can always increase their NER by increasing the share of short-term interbank loans. If $\Pi_G - \Pi_B > \Pi_G \Pi_B$, there is a positive relationship between the share of short-term interbank borrowing and the tendency of borrowing banks to take more risk when they try to maximize their net expected return.

CHAPTER FOUR

MACROECONOMIC CAUSES OF BANKING DISTRESS: EVIDENCE SINCE THE 1990s

4.1 Introduction

In the late 1990s, especially following the Asian financial turmoil, a flourishing body of literature investigating the determinants of banking crises started to emerge, partly as a result of central banks' effort to establish an early warning system (e.g., Caprio and Klingebiel 1996, 2003; Eichengreen and Rose 1998; Demirgüç-Kunt and Detragiache 1998, 2000; Kaminsky and Reinhardt 1999; Hutchison and McDill 1999; Edison 2000). These papers have contributed tremendously by investigating the common macroeconomic roots of banking crises which occurred during the early 1980s and 1990s. In particular, they find that banking crises are preceded by economic recession and therefore can be predicted by macroeconomic indicators such as a dramatic fall in real GDP growth rate. Paradoxically, other studies such as those by Honohan (1997) and Juan (1996) are inclined to blame factors other than macroeconomic shocks, e.g. defects in the banking sector itself, for the systemic banking crises.

This chapter performs an empirical study verifying the macroeconomic determinants of banking crises proposed by earlier studies. In practice, it finds that the earlier studies share a common problem in defining the dependent variable of their model – the crisis dummy variable. All of the existing studies use indirect indicators to detect crises. In particular, the majority follow "event studies" where a banking crisis is defined when a combination of events including bank closures, forced mergers and take-overs and large-scale government bailouts become publicised in the media. Other studies like Hagen and

Ho (2003) propose a weighted average to quantify the banking sector difficulties. They define banking crises as significant tensions in the money market caused by bank runs, the drying up of interbank lending, or large-scale support by the central bank or a combination of the three. However, as the latter two factors are measured by money market interest rates and the intervention of the central bank in terms of credit injections, the identified dates may merely represent normal implementation of monetary policy rather than banking sector problems.

Both types of these studies opine that banking sector difficulties have often been widely identified for some time before that point. The direct indicator reflecting deterioration of banks' asset quality is not used in those studies, largely because stock market data are not available from emerging markets in the early 1980s and sector indices of systemic implications are not available until the early 1990's, even for many of the developed markets. Nevertheless, using stock indices available since the 1990s, the chapter is able to re-examine the macroeconomic causes through direct crisis identification. Banking crises are identified by the chapter as when there is an abnormal fall in the banking industry stock indices, independent of general market movement.

In addition to crisis identification, the chapter differs from existing studies in classifying the dependent crisis dummy into a pre-crisis period, a post-crisis period, and a crisis period. In doing this, the chapter aims to verify the assertions of earlier studies regarding macroeconomic indicators prior to banking crises and investigate their movement in relation to the protracted post-crisis period. As Hardy (1998) noted, some of the macroeconomic variables typically display a distinctive boom and bust pattern, both in the lead-up to an episode of banking system distress and while the episode is unfolding. Moreover, the "pre-/post-crisis bias" is ignored in some existing studies, which probably contributes to the insignificance of the individual explanatory variables.

The results of the current empirical studies corroborate the analysis of Hardy (1998) and indicate a "boom and bust" pattern around a crisis. Specifically, they imply that the economy still "thrives" in the "pre-crisis" period in terms of increasing GDP growth. In contrast to earlier empirical studies, the economic downturn in terms of a fall in GDP growth is generally associated with the post-crisis period. As the "bust" parts appear to be shifted afterwards in this chapter, it is concluded that the inconsistency of results is very likely due to imprecise crisis identification of earlier studies. The existing studies might often identify crises too late on the basis of indirect symptoms.

The rest of the chapter is structured as follows. Section 4.2 reviews early literature on macroeconomic causes of banking crises and their approaches to crisis identification. Section 4.3 presents the current empirical study aimed at verifying the macroeconomic roots of banking crises. It uses the bank stock index to identify crises and provides a comparison with existing approaches. The section also explains the multinomial logit model and empirical specification of the crisis analysis. Then, empirical results are analyzed in detail in terms of each macroeconomic variable under investigation, comparing them with earlier studies. Section 4.4 concludes.

4.2 Literature Review

4.2.1 Macroeconomic Causes of Banking Crises

Many discussions of banking distress start with an analysis of the specific characteristics of the bank that have failed, which involves poor risk management, malfeasant behaviour and the loophole of a regulatory system that permits those mistakes. However, when trying to investigate systemic distress in which a substantial fraction of the banking sector is endangered, economists agree that this focus is incomplete and potentially misleading. In particular, Hausman (1996) argues that the observed shortcomings of failed banks do not explain the crisis, and that banks fail as the result of the crisis. He uses a metaphor to support his argument: "Chains break at their weakest link……strengthening weak links in the chain only works if one succeeds in identifying the weakest link before it snaps, and even then will accomplish nothing more than causing the chain to break at another link if the tension on the chain is sufficiently high." Thus, he implies that it is more important to identify the tension on the chain than to identify the weakest link. In his metaphor, tension placed on the chain refers to macroeconomic developments.

Other studies (Gorton 1991, Honohan 1997, Hardy and Pazarbasioglu 1998, Demirgüç-Kunt and Detragiache 1998, Kaminsky 1999) echo this argument and point out that banking crises are preceded by economic recession and therefore can be predicted by macroeconomic indicators. Slow GDP growth is regarded in these studies as harming the balance sheet of banks through two channels. One channel is through bank liabilities when depositors withdraw large amounts from all banks. Gorton (1991) believes that panic withdrawal by depositors is not just random manifestation of "mass hysteria", but is systemically related to the aggregate information that changes their perception of risk. Bank runs occur as features of nearly every severe business cycle downturn because depositors expect a large number of banks to fail during recessions. The other channel is through deteriorating bank assets, which is more acknowledged by modern theory (see Hardy and Pazarbasioglu 1998, Demirgüç-Kunt and Detragiache 1998, Kaminsky 1999) of bank failure. This happens as non-performing loans increase systematically due to the fact that adverse shocks affect the solvency of bank borrowers, whose impact cannot be perfectly diversified by banks in an economy that is in general distress (Hagen and Ho 2003).

However, Honohan (1997) is sceptical that banking systems collapse because of macroeconomic shocks, as some of them have survived very severe macroeconomic shock. He contends that the chain breaks as the result of the homogeneous weakness of all links. Moreover, he considers the macroeconomic disturbances to be endogenous, which, to some extent, are caused by the banking systems themselves. The systemic distress in the banking sector originates from the economic boom preceding business slowdown, where banks riding on a wave of optimism overlend to projects which have poor long-term prospects. Temporary success brought in by the weight of money lent may bid up the asset price and thereby draw further lust from beneficiaries and would-be beneficiaries. The situation does not occur as the result of activities of individual banks that normally learn to observe others and adopt market norms for lending. It comes from the herding behaviours which lesson the usual prudent risk management and leads to a self-fulfilling shift in the views on sectoral creditworthiness, especially with regards to the property sector. As wealth effects generate a consumption boom, it also leads to an exaggerated current account deficit, then real exchange rate appreciation, a loss of competitiveness, and finally a slowdown in growth.

With a moderate perspective, Hardy (1998) opines that, although the macroeconomic variables are worth watching closely, they are far from reliable. He notes that some of these variables typically display a distinctive boom and bust pattern, both in the lead-up to an episode of banking system distress and while the episode is unfolding.

> "……after rising rapidly, real GDP, consumption, and, especially, investment start to decline; an acceleration in inflation is suddenly reversed; credit from the banking system to the private sector builds up rapidly, peaks, and then contracts; real interest rates increase steadily; and the real effective exchange rate appreciates and then depreciates. In the lead-up to a crisis, banks often rely increasingly on foreign borrowing, which then dries up."

Therefore, his study implies that banking crises are most likely associated with, but not necessarily preceded by, economic recession.

4.2.2 Existing Empirical Studies

4.2.2.1 Candidate Indicators and Variables

The Asian financial crisis in 1997 gave impetus to a flourishing body of empirical literature on the macroeconomic determinants of banking crises. Demirgüç-Kunt and Detragiache (1998), Hardy and Pazarbasioglu (1999), and Kaminsky and Reinhart (1999) show that shocks that adversely affect the economic performance of bank borrowers and whose impact cannot be reduced through risk diversification should be positively correlated with systemic banking crises. This is because the value of banks' assets could drop and fall short of banks' liabilities (bankruptcy) when bank borrowers become unable to repay their debt. The shocks associated with banking crises highlighted in these studies include output downturn, and declines in asset prices. Their findings are consistent with earlier studies in Gorton (1988) and Caprio and Klingebiel (1996).

Even in the absence of lower performance of bank borrowers, these studies find that high domestic real interest rates increase the possibility of banking crises (Reinhart 1999, Demirgüç-Kunt and Detragiache 1998, Hardy and Pazarbasioglu 1999, Hagen and Ho 2003 etc.). This is because, for banks, the rate of return on assets (usually at a fixed rate for a long-term loan) cannot be adjusted at the same pace as the deposit rate. When there is an abrupt increase in the official rate, lending rates would fall short of the rate that banks have to pay to their depositors, thereby reducing profits or imposing losses on banks. In fact, all banks are exposed to some degree of interest rate risk because maturity transformation is one of the typical functions of banking systems. As pointed out by Demirgüç-Kunt and Detragiache (1998), banks are especially vulnerable to such risk in economic recession when various other problems, including a sharp decrease of asset price and capital outflow, place them on the brink of insolvency. In the circumstances, it is hard for banks to refinance in a market that lacks confidence. Moreover, attempts by the banks to call-in loans or refuse to renew them leads to financial distress of the banks' borrowers and a downturn in aggregate demand, thereby pushing banks into a vicious circle.

However, Hardy and Pazarbasioglu (1998) and Honohan (2000) report a boom in bank lending to the private sector prior to banking crises, with a further decline during the crisis. Overborrowing cycles leading to crises are also found in Kaminsky (1999), Kaminsky and Reinhart (1999) and Hagen and Ho (2003, 2007). Honohan (1997) argues that the credit expansion in the prolonged boom is often financed by additional base money, which is the reason why capital inflows often present in early stages. He implies that, when the capital inflows come to a stop or experience a sharp unwind, the banking system caves in. As Goldfajn and Valdes (1995) argue, the introduction of intermediation by banks in the capital flow both attracts capital inflows by offering liquidity to the customers and creates all its side effects: allowing possibilities of a run on their assets. The latter places banks under severe liquidity pressure, and thereby leads to a fire-sale of their assets. Forced sale in the circumstances may not be easy, as the asset market already reaches an impasse. The selling pressure in the asset market causes a sharp deflation of asset prices (including collaterals), and thereby pushes borrowers and banks into financial distress. Eichengreen and Rose (1998) and Kaminsky and Reinhart (1999), Zhuang & Dowling (2002), Demirgüç-Kunt and Detragiache (1998) and Hardy and Pazarbasioglu (1999) demonstrate that the vulnerability to capital outflows can be reflected in overvaluation before crisis, depreciation during a crisis, and a decline in foreign currency reserves relative to M2 money.

Moreover, as countries vary in their vulnerability to banking crises, Hardy and Pazarbasioglu (1999) and Hagen and Ho (2003) also take into account the institutional factors. They believe that a financial sector lacking a sound legal system and the efficiency of law enforcement is more likely than otherwise to experience banking crises. These factors can be reflected by lower GDP per capita.

4.2.2.2 Methodologies and Findings

Based on the methodology proposed by Diebold and Rudebusch (1989), and Stock and Watson (1989) for leading indicators, Kaminsky and Reinhart (1999) propose a Leading Indicator approach for currency and banking crises. They investigate empirically a list of candidate variables discussed above and determine the thresholds for each variable that signals warning for crises. This threshold is the value of the variable that minimizes the ratio of false alarms to genuine alerts of banking crises over a horizon of 24 months prior to the crises. However, the indicator studies do not allow for checking the individual contribution of each variable to the crisis and there is no way to include regional differences. Later studies overcome these problems and adopt a Limited Dependent Model Approach for estimating the incidence of crises which can be regarded as a binary discrete event (1 for crisis or 0 for non-crisis). In particular, Eichengreen and Rose (1998), Demirgüç-Kunt and Detragiache (1998), Hagen and Ho (2002, 2007) and

Hutchison and McDill (1999) use either a probit or logit model to verify the marginal contribution of individual indicators to banking crises.

Nevertheless, the binomial model also has limitations. Hardy and Pazarbasioglu (1999) argue that crises are often defined to start when intervention became necessary, but often the difficulties might have been widely recognised and have caused serious disruption for some time before then. Therefore, economic behaviour in the run-up to the onset of an episode may differ significantly from that in tranquil times. Taking account of this factor would improve the predictive power of the leading indicators independently of what only becomes clear in the crisis year. Practically, they estimate a multinomial model and define a discrete variable that takes the value of 2 in the event of a crisis, a value of 1 in the previous year, and zero otherwise.

Table 4.1 summarises the findings of existing empirical studies. To facilitate comparison, the table lists the explanatory variables that are commonly used in these studies. Specifically, both indicator studies and binomial model studies find that real GDP growth tends to be negatively associated with banking crises. However, estimating the multinomial model, Hardy and Pazarbasioglu (1999) find that the decrease in real output is insignificantly related to the incidence of pre-crisis period. It only becomes negative during the crisis period. Inconsistency in the signs of coefficients also appears in domestic real interest rates, overvaluation, and credit rate growth, leading to the occurrence of banking crises. This indicates that sometimes lower interest rates, undervaluation and lower credit rate growth are found prior to or during crises, in contrary to the predictions of theories explained in the previous section. As the following sections develop, the chapter attributes the inconsistency largely to the differences in defining the start of crises. The existing studies may identify the crises too late so the macroeconomic variables display their "down-turn" movement in the pre-crisis period. After the outbreak of crises, the acceleration in inflation reverses (as reflected in interest rate as well), bank credit contracts and real effective exchange rate depreciates.

4.2.3 Identification of a Banking Crisis

Correct identification of the emergence of banking crises is essential to their causality analysis. This section reviews two approaches to identifying crises in existing studies: event studies and money market pressure index (MMP). As will be explained below, the event studies which are most widely used tend to identify crises too late or too early, while the MMP index approach may detect events (monetary policy change) other than banking crises.

4.2.3.1 Event Studies

Event studies rely on a combination of events to define the onset of a banking crisis. Kaminsky and Reinhart (1999), for instance, mark the beginning of a banking crisis by two types of events: "(1) bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions; and (2) if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions) that marks the start of a string of similar outcomes for other financial institutions." As their definition makes no distinction between bank fragility in general and fully-fledged crises, Demirgüç-Kunt and Detragiache (1998) shortlist their results by imposing one of four conditions: "(1) the ratio of non-performing assets to total assets in the banking system exceeded 10 percent; (2) the cost of the rescue operation was at least 2 percent of GDP; (3) banking sector problems resulted in a large-scale nationalization of banks; (4) extensive bank runs took place or emergency measures such as deposit freezes, prolonged bank holidays, or generalized deposit guarantees were enacted by the government in response to the crisis."

However, Kaminsky and Reinhart (1999) and Hagen and Ho (2004) admit that the disadvantage of this approach is that it may date the crises too late because the severe financial problems usually emerge well before any bank run, closure or merger, government intervention or rescue. Hagen and Ho (2003) also point out that the decision is usually arbitrary on whether an event is large enough to be a systemic crisis; and the criteria is not always consistent across studies. As illustrated in Table 4.2, countries recorded as having a crisis in one study are recorded with no crisis in other studies. Moreover, event studies often limit themselves to low frequency annual data, making it difficult to forecast future crises to a precise level.

4.2.3.2 Money Market Pressure Index (MMP)

Hagen and Ho (2004) propose an alternative approach to enable consistency and high frequency data. Motivated by approaches to identify currency crises, they detect banking crises when there is a sharp increase in the banking sector's aggregate demand for central bank reserves. They suggest it is very likely that high liquidity demand comes from bank runs, a sharp decline in the quality of bank loans, or the deadlocked status of the interbank market. In these situations, they argue that central banks will either inject additional reserves if the short-term interest rate is targeted to be fixed, or the money market rate will rise if the reserves are the operating target. Based on these assumptions, they develop an index of money market pressure (MMP) which measures the weighted average of changes in the ratio of reserves to bank deposits and changes in the short-term real interest rate:

$$MMP_t = \varpi_{\Delta ratio} \times \Delta ratio_t + \varpi_{\Delta RMMR} \times \Delta RMMR_t \tag{4.1}$$

where the $ratio_t$ denotes the ratio of total reserves held by the banking system to total non-bank deposits in the banking sector; in a period of high tension in the money market, they explain this ratio increases either because the central bank makes additional reserves available to the banking system, or because depositors withdraw their funds from the banks. Moreover, $RMMR_t$ denotes the money market rate in real term; Δ denotes difference operators; $\varpi_{\Delta ratio}$, $\varpi_{\Delta RMMR}$ denote the inverse of the standard deviation of the two components respectively. Hagen and Ho (2004) define the onset of a banking crisis as a period in which the value of the MMP index exceeds its country-specific 98.5 percentile.

Compared with event studies, MMP indices improve in precision and consistency while avoiding arbitrariness. However, the approach has several obvious shortcomings. Firstly, Hagen and Ho (2004) admit that a systemic panic run on banks is seldom witnessed in modern banking crises following the introduction of explicit deposit insurance (an assertion also made by Glick and Hutchinson (1999), Hardy and Pazarbasioglu (1998), Kaminsky and Reinhart (1999); Secondly, given that bank deposits will not change dramatically during crises, an increase in the interbank rate and credit injection of central banks as components of the index may well be due to other aspects than indicators of interbank market dry-up and central bank's liquidity support banking crises. An increase in the money market rate could be merely a pass-through effect of monetary policy targeting inflation rates. Hence, the IMP approach could mislead by inventing too many crises that do not exist (Type II error).

4.3 An Empirical Analysis of Banking Crises

4.3.1 Identifying Crises Using The Bank Stock Index

Kaminsky and Reinhart (1999) state that banking crises arise directly from the protracted deterioration of banks' asset quality, be it from a collapse in real-estate prices or increased bankruptcies in nonfinancial sectors. Thus, changes in bank asset prices or nonperforming loans could be measured to indicate the beginning of the crisis. However, the previous practices commonly use indirect indicators to signal a banking sector problem. Researchers justify the usage of these methods on the grounds that the direct indicators are either not available or are difficult to interpret in the early studies (Hagen and Ho 2003). Nonperforming loans are normally released on an annual basis and the figure may be less informative due to banks' incentive to hide their problems as long as possible. For the sample period that starts from the early 1980's, there seems to be no stock market data available in emerging markets. Furthermore, the sector indices are not available until the early 1990's even for many of the developed markets.

Using stock market data since the 1990s, the following sections aim to identify the onset of banking through direct indicators and analyze the difference from the previous approaches.

4.3.1.1 Bank Stock Index (IBS)

Stock market data have been applied in many studies to signal banks' problems (Krainer and Lopez 2003 and 2004; Vesala and Vulpes 2004; for example). However, the application of this chapter is different from these studies in two aspects. Firstly, it is concerned more with the entire banking industry than with individual banks. Thus, the chapter uses bank industry indices in preference to individual bank stock prices. Moreover, individual banks' balance-sheets are not involved in the causality analysis. Secondly, the abnormal falls in the industry indices are used to generate limited dependant variables in the crisis analysis model.

The chapter defines the falls in terms of the percentage change of the current index to its value in the previous period. However, complications may arise as the industry index makes no distinction between general market movements and idiosyncratic single-sector movements. Crises could be falsely identified if the general movement is led by sectors other than the banking sector. To extract the effect, the percentage change of the banking industry index is regressed against that of the general market index. The residuals obtained are treated as the crisis index. The regression and the bank stock index (IBS) are shown in equations (4.2) and (4.3) below:

$$R_{Bt} = \beta_1 + \beta_2 R_{Mt} + resid_t \tag{4.2}$$

$$IBS_t = resid_t \tag{4.3}$$

where R_{Bt} and R_{Mt} respectively denote the percentage change of the bank industry index and market index; and $resid_t$ denotes the residual values. The onset of a banking crisis is identified when the IBS index is lower than its 0.5 percentile, i.e. the stock index of the banking industry plunges to a level lower than 99.5% of other changes in the sample period.

The crisis threshold is tighter than that of the MMP (98.5 percentile) because relaxing it to 99 or 98.5 identifies too many episodes crises, while tightening the threshold tends to miss some of the well-known crises recorded in event studies (such as 1997 for Thailand and the Philippines).

Moreover, the thresholds to identify crises are country specific. An alternative to this is to pool the data from all countries and apply the same threshold for all. However, as indices across countries are varied in their volatility, which implies different financial and macroeconomic environments, pooling the panel data takes the risk of ignoring crucial crises in countries with relatively lower volatility.

4.3.1.2 Applications

This section compares the results of the current IBS index with those of event studies, the MMP index approach. Quarterly data are selected spanning from 1990Q1 to 2005Q4. The stock market data is collected from Thomson Datastream and MMP indices are calculated using the same data source as Hagen and Ho (2003, 2007), i.e. IMF International Financial Service. The results are compared with a number of event studies and the World Bank online database up to 2003 (an update of Caprio-Klingebiel 1996, 1999). The choice of country is largely based on data availability, and whether the country has experienced banking crises during the sample period. The choice is also restricted by the availability of macroeconomic explanatory variables over the sample period. As a result, a small sample of nine countries is selected: Australia, Denmark, Korea, Malaysia, Mexico, the Philippines, Thailand, the United Kingdom and the United

States. Nevertheless, the sample covers both developed and emerging economies diversely located.

Table 4.2 presents the dates identified by the IBS indices comparing with those identified by event studies and the MMP approach. All crisis dates recorded in event studies have been captured in the results of the IBS approach, allowing for two year lags or leads. Despite its drawbacks, event studies can still be used as a benchmark because the method provides accurate records of historical events and one can be sure that banking distress or crises are around the time recorded. However, differing from the wide-scale financial crises in Asia around 1997 and in Latin America around 1995, the dates identified for developed countries are less severe in nature and should be regarded more as "distresses" than as crises. Nevertheless, they have systemic implication and reflect an abnormal decrease in asset quality.

The IBS index identifies additional crises which are not recorded in event studies. These include the years of 1999 and 2002 for Australia, Denmark, and the US. There are two explanations for these discrepancies. Firstly, the sample period of many of the event studies is until 1997 and recorded events after that date are unavailable. Secondly, the additional crises identified by IBS are "too small" in magnitude to be recorded in other studies such as the World Bank database, which usually requires at least 0.5% of fiscal cost. Crises such as the US Long-Term Capital Management (LTCM) that required a $3.75 billion bail-out during 1998 and 2000 are resolved by the private sector without any government spending. Moreover, the aftermath of the 1997 Asian Crisis, the Russian

Crisis in 1998 and the burst of US dot-com bubbles from 2000 to 2002 all led to a world-wide impact on bank loan quality during those periods. Likewise, though not founded in event studies, the dates of 1994Q3 in Malaysia and 1991Q2 and 1994Q1 in the Philippines by the IBS approach are not identified ungrounded. These dates are recorded in other literature or financial newspapers. It is found that the financial sector in Malaysia experienced a capital outflow of the same level between 1994 and 1995 as in the financial crisis in 1997, while in the early 1990's, the Philippines faced a severe power crisis (Dornbusch 2001, Austria 1999, Financial Times 2008, Jakarta Post 2001). Therefore it is very likely that the banking sector in Malaysia and the Philippines survived a period of distress in 1994, without visible bank failure or government interference that could be recorded in the event studies. Furthermore, these dates overlap with those identified by the MMP approach, suggesting "money market pressure" around the crises. However, the chapter is cautious in applying the MMP, since the approach could invent false crises such as 1996Q3 in Australia, 2004Q1 in Denmark, 1991Q2 in Korea. These dates only reflect monetary policy targeting high inflation and are misrepresented as bank crises (Type II error).

4.3.1.3 Limitations of the IBS Approach

There may be two possible objections to this method. Firstly, similar to the MMP approach, the threshold for identifying crises in the IBS approach is arbitrary. However, there is apparently no better way to resolve it. Hagen and Ho (2004) tried to endogenize the choices of crisis threshold by using the Markov switching model, but find that the method is sample-dependent, tends to invent many more crises, and is less robust to different model specifications. The chapter repeats the endogenization process in Hagen and Ho (2004) and presents the results in Appendix 4.1. As Table 4.9 indicates, the Markov switching model invents too many crises in the case of several countries, especially the UK where crises are identified in almost every period of the sample. Moreover, for some countries where few crises are identified, the results fail to include well-known crisis episodes recorded in the event study, e.g. 1997-1998 crises in Korea, the Philippines and Thailand are misidentified.

Secondly, it could be argued that the dramatic drop in stock prices could just be due to irrational short sell and speculation of investors, the behavior of which has no direct link with the deteriorating quality of bank assets. This occurs when, for example, information is released about the failure of one or two large banks or they seek a bail-out from the government. As a consequence, the investors sell shares in all other banks for fear that the problems are linked and contagion may follow. Nevertheless, if the self-fulfilling panic short-sell actually causes the prices of banks' assets to plummet on a sector-wide scale, this is a de facto crisis and should be identified as such.

4.3.2 Macroeconomic Causes of Banking Crises

4.3.2.1 Econometric Approach

The chapter follows the existing studies and adopts the Limited Dependent Model Approach to analyze the relationship between macroeconomic variables and banking crises. A traditional linear model is not appropriate here because the banking crises/distresses are discrete events distinct from those which can be measured by continuous variables. Specifically, the chapter uses a multinomial logit model for estimating more than two responsive categories. As explained in later sections, the responsive categories consist of four unordered nominal variables, i.e. crisis (y=1), pre-crisis (y=2), post-crisis (y=3), and tranquil period (y=4). Formally, the model is expressed as follows:

$$\Pr(y_t = j) = \frac{\exp\left(\sum_{k=1}^{K} \beta_{jk} x_k\right)}{1 + \sum_{j}^{J-1} \exp\left(\sum_{k=1}^{K} \beta_{jk} x_k\right)} \tag{4.4}$$

Equation (4.4) produces Prob(y=j), where j=1,2,…J-1 for J numbers of categories (here J=4) and *k* for distinguishing *x* variables. Prob(y=J) can be derived by taking 1-[Prob(y=1)+…+Prob(y=J-1)]. The unknown parameters β_j's are estimated by maximum likelihood. The model can be also expressed in logit form:

$$L = \log\left[\frac{\Pr(y = j)}{\Pr(y = J)}\right] = \exp\left(\sum_{k=1}^{K} \beta_{jk} x_k\right) \tag{4.5}$$

where the left-hand side is a log odds ratio, and the right-hand side gives the marginal effect of x_k on the odds indicated by $\exp(\beta_{jK})$. Therefore, an estimated coefficient β_{jk} does not indicate a change in the probability of a banking crisis for a unit change in the value of a corresponding explanatory variable. Instead, it measures the impact on the estimated Logit L, with all other x_k variables held constant. If a marginal effect on the probability is calculated, it is given by:

$$\frac{\partial \Pr(y=j)}{\partial x_k} = P_j\left(\beta_{jk} - \sum_{j=1}^{J-1} P_j \beta_{jk}\right) \tag{4.6}$$

Thus, the marginal effect on $\Pr(y=j)$ depends on the initial values of all explanatory variables in P_j (i.e. equation 4.4). As equation (4.4) is not linear in x_k, caution should be exerted in interpreting the magnitude of the coefficient β_{jk}. This is because, as explained by Demirgüç-Kunt and Detragiache (1998), when a country has an extremely high (or low) initial probability of crisis, a marginal change has little effect on its prospect, while the same marginal change has a greater effect if the country's probability of crisis is in an intermediate range. As the chapter is more interested in the direction of the change from x_k to $\Pr(y=j)$, it will avoid the magnitude bias and only interpret the sign of the coefficient β_{jk}.

4.3.2.2 Dependant variables and Pre-/Post-crisis Bias

Two groups of dependent variables were defined for use in the estimation process:

(1) A dummy variable (designated y_1) takes 1 when banking sector difficulties emerged, 2 in the preceding periods, and 3 otherwise (succeeding periods eliminated);

(2) A dummy variable (designated y_2) takes 1 when banking sector difficulties emerged (identified by the IBS index), 2 in the preceding periods, 3 in the succeeding periods, and 4 otherwise.

The approach of treating the pre-crisis period, post-crisis period and the crisis period as separate events has several considerations. Firstly, the assertions of previous studies can be empirically verified that banking crises are preceded by economic recession and therefore can be predicted by macroeconomic indicators. The existing studies (described in section 2) argue that, before the dramatic fall of bank asset prices, the difficulties might have been widely recognised and might have caused serious disruption for some time beforehand. Secondly, as the post-crisis period is normally regarded as being part of the crisis itself, the relationship between macroeconomic variables and the incidence of this period is of interest. Thirdly, Hardy and Pazarbasioglu (1999) and Demirgüç-Kunt and Detragiache (1998) point out that the economic behaviour in the run-up to and after the declared start of an episode may differ significantly[16] from that displayed in normal times. Therefore, no distinction between the pre-/post-crisis periods and the non-crisis period

[16] However, the value of the dummy dependent variables does not depend on the significance of this difference. Pre-crisis, crisis, post-crisis and other periods are categorized as they vary in the position of the time-line.

could lead to bias in the empirical results. The difference between the pre/post-crisis period and tranquil times could be averaged out and inclines to conclude insignificance of the individual explanatory variables in the empirical results.

The four category responsive model is based on the three category model of Hardy and Pazarbasioglu (1999), who take the "pre-crisis" bias into consideration. As shown in Table 4.3, most binomial studies ignore such bias except for Eichengreen and Rose (1998) and Hutchison and McDill (1999), who eliminate all observations around crises. However, their approach, as implied by Hardy and Pazarbasioglu (1999), fails to establish the predictive power of the leading indicators independently of what is only known in the crisis year Demirgüç-Kunt and Detragiache (1998) use two approaches to control for post-crisis bias and opine that both have their drawbacks. Firstly, eliminating all observations following the crises tends to leave fewer observations for estimation. Secondly, identifying the end of crises allows the inclusion of all observations, but determining when a crisis ends is quite difficult and somewhat arbitrary. Considering these drawbacks, Hagen and Ho (2002) set different window widths (8/12/16 quarters) to eliminate observations following a crisis.

Based on existing studies, this chapter adopts two approaches to deal with pre/post-crisis bias. The first group, as explained in statement (1), estimates a three-category logit model following Hardy and Pazarbasioglu (1999), but eliminates the post-crisis observations. The second group investigates a four-category logit model, as explained in statement (2).

However, determining the widths of windows is very difficult. It amounts to identifying the start of disruption and the end of crises, the arbitrariness of which cannot be avoided not only in this chapter[17]. The existing studies in Table 4.3 seems to display different opinions on how long a crisis normally lasts or whether the window is symmetrical around the crisis. Nevertheless, it can be concluded, from the studies which have a clear figure for the window width, that these studies commonly agree that the window width ranges from two years (or eight quarters) to four years (16 quarters) around the onset of crises. Due to the limitation of total observation, the chapter chooses a window width (eight quarters) within the range set to satisfy the condition that, during the sample period, countries have less disruption time than a non-crisis period, an assumption reasonable for countries in this sample.

4.3.2.3 Choice of Explanatory Variables

The choice of explanatory variables is both guided by existing literature discussed in previous sections and by data availability. A complete description of the data and their sources are available in Table 4.4. Table 4.5 presents the sample mean of explanatory variables and their standard errors. Five groups of variables are used as indicators of banking sector problems. In the first group, the chapter uses real GDP growth rate (GROWTH), the domestic real interest rate (RMMR) and the inflation rate (INFLATION) to capture the macroeconomic environment during crises. Slow growth harms the balance sheet of banks through deteriorating bank assets. This happens because non-performing loans and defaults of borrowers increase systematically during

[17] In fact, no existing studies under investigation can avoid the arbitrariness of choosing the window width.

recessions. Besides, inflation could reflect macroeconomic mismanagement which adversely affects the economy, and thus the banking sector. High short-term real interest rates also affect banks' balance sheets, as banks cannot adjust their lending rates (income) quickly enough to match the same pace as the deposit rate (cost), making banks less profitable or causing them to lose money.

The second group of variables relates to a country's low external competitiveness and vulnerability to capital outflow. The banking crisis is usually linked with a currency crisis (Kaminsky and Reinhart 1999). As many banks denominate their liabilities in foreign currency (or borrow from overseas) and lend domestically, the collapse of the exchange rate could bring huge losses to banking sectors. Of course, the excessive foreign exchange risk exposure could also affect bank borrowers. The risk is measured by depreciation in the nominal exchange rate (FOREX) and the deviation of the real exchange rate from its trend (OVREER), i.e. over-valued currency.

The third group of variables test whether systemic banking sector problems are associated with sudden capital outflows. The sudden reversal of capital could place banks and their borrowers under severe liquidity pressure, and thereby lead to a fire-sale of their assets and a sharp deflation of asset prices (including collateral). M2/reserves ratio (M2/reserve) is used to capture capital outflow. The high value of this ratio around crises indicates increasing selling of domestic currency and therefore diminishing foreign reserves. Besides, earlier studies suggest that excessive short-term foreign debt at short maturities (FODEBT) will increase the vulnerability of a country to external shocks.

The fourth group of variables describe the over-lending cycle. According to earlier studies, banking crises are preceded by strong credit growth (CREDITGRO). This is because, during an economic boom, banks ride on a wave of optimism, over-lending to projects which have poor long-term prospects. When the economy slows down, the banking sectors have to face the bust of the cycle. Moreover, the rapid growth in credit is usually fuelled by monetary expansion.

The fifth group defines the institutional variables. Firstly, it uses GDP per capita (GDPCAP) to reflect the soundness of a legal system and the efficiency of law enforcement. Demirgüç-Kunt and Detragiache (1998) and Hagen and Ho (2003) argue that a country with a weak legal framework or/and inefficient law enforcement tends to breed problems in the banking sectors more easily. Finally, the capital outflow variables are multiplied with regional dummy variables (emerging markets) to construct the regional effect factor. Calvo and Reinhart (1999) stressed that the sudden stop or reversal of capital is virulent, especially in emerging markets such as the Argentinean crisis in the early 1980s, the Mexican crisis in 1994 and the Asian crises in 1997.

4.3.3 Empirical Results

Table 4.6 and Table 4.7 contain the main results of the econometric investigation. Table 4.6 reports the estimation result and standard errors for the dependent variable y_1, which takes on a value of 2 in the crisis period, and 1 in the pre-crisis period. The regressions use the panel that excludes the eight quarter post-crisis observations. Table 4.7 reports the same regressions for the dependent variable y_2, in which post-crisis observations are included and take on the value of 3. In each table, the first regression includes only the macroeconomic variables, while the second regression adds variables capturing institutional features and regional effects.

4.3.3.1 Overall Performance and Prediction Accuracy

The quality of model specification is assessed based on log likelihood value, Akaike Information Criteria (AIC) and in-sample classification accuracy. The chapter uses the former two to compare models with different degrees of freedom. As a result, the specification in both Table 4.6 and Table 4.7, including the institutional features and regional effects, seems to perform better than those which only include macroeconomic variables (higher log likelihood value and lower AIC). To assess the prediction accuracy, both tables report the percentage that are correctly classified of crisis (y=2), pre-crisis (y=1), post-crisis (y=3), non-crises (y=0) and the percentage of total observations that are correctly classified. From both tables, it appears that the models do not perform very well in terms of predictions. Although the percentages of total observation that are correctly classified are quite high, above 70%, the accuracy largely comes from the correct classification of the non-crisis (y=0) periods, the percentage of which are over 90% in both Table 4.6 and Table 4.7. In contrast, the prediction accuracy for pre-crisis, crisis and post-crisis period is low, around 50% for the pre-crisis period in Table 4.6 and about 25% for the pre-crisis period in Table 4.7. In particular, the incidence of crisis breakout can be hardly be predicted by macroeconomic variables, with about 4% of correct classification in Table 4.6 and close to 0% in Table 4.7. Therefore, the results agree with the claim by Hardy (1998) that the macroeconomic variables are far from being reliable enough to predict the onset of banking crises. Moreover, the higher accuracy in predicting pre-/post-crisis (y=1 or 3) than crisis (y=2) lies in the fact that more individual explanatory variables are significant (such as inflation, INFL and over-valuation of the real effective exchange rate, OVREER) as explained below.

4.3.3.2 Performance of Individual Explanatory Variables

Despite a poor overall performance and low accuracy in predicting crises, the econometric results indicate a "boom and bust" pattern around crises (particularly in GDP growth, inflation, over-valuation of REER, foreign debt), corroborating assertions of Hardy (1998) mentioned earlier. Specifically, Table 4.6 and Table 4.7 suggest:

- The onset of banking crises is also the turning point of the business cycle. Banking distress is associated with a fall in real GDP growth. However, the fall is not contemporaneously significant, but becomes apparent after the crises break out. In contrast to previous studies, the probability of pre-crisis incidence is increased by a rise in real GDP growth. There is a similar pattern for inflation (INFL) which rises before crises and falls following the outbreak of crises.

- The real interest rate (RMMR) is highly significant in all the specifications and has the expected sign. Thus, a high interest rate seems to be one of the most reliable indicators of the banking sector. Together with increasing inflation before crises, the results confirm the theories that banks are vulnerable to nominal and real interest rate shocks.

- The coefficient of real effective exchange rate (PREER) is not significant but including this variable improves the overall performance of the models. In addition, it shows the expected signs to indicate that banking crises are associated with a sharp decline in the real effective exchange rate.

- In contrast to PREER, there is a persistent and robust tendency for the real exchange rate to deviate from its trend (OVREER) before the onset of crises. The sign of coefficients accords with the prediction of the theory that over-valuation in exchange rates is a leading indicator of banking crises (positive sign) and the depreciation of the exchange rate from its trend (negative sign) worsens the balance sheets of the banking sector which is already suffering, although the latter is only marginally significant.

- M2 to reserve ratio (M2RES) and foreign liabilities (DFODEBT) of banks, both indicating a capital account problem, show consistent signs of the theory of Honohan during the pre-crisis period. Large foreign debt, and therefore less domestic currency and massive foreign reserves concentrated before crises increase the vulnerability of a country's banking sector to external shocks. However, although not significant, the coefficients of the two variables go in the opposite direction during the crisis period, indicating the actual occurrence of capital outflow, which is reflected in increasing M2 to reserves ratios and decreasing foreign liabilities.

However, the negative sign of M2 to reserves ratios in the post-crisis period is less likely to indicate banking sector problems. This could be due to a decrease in M2 as banks are unwilling to expand credit during crises.

- As expected, credit growth (CREDGRO) has a positive sign before crises and a negative sign following the crises. However, the variable is only significant in Table 4.7, indicating that there is a strong "boom and bust" pattern around banking crises. The pattern coincides with other variables such as GDP growth, over-valuation of exchange rates, and banks' foreign debt. This also accords with Demirgüç-Kunt and Detragiache, who find that credit expansion funded mainly by capital inflows, leading to overinvestment, seems to be a critical factor leading up to the crisis.

- The inclusion of institutional variables improves the overall performance of the estimations and the absolute values of estimated coefficients become larger when the regional variables are included. Both banks' foreign liabilities and M2 to Reserve ratios, when interacted with a dummy of developing countries (DEVDFOBEDT and DEVM2RES), are significant and negatively associated with pre-crises incidence. It indicates that banks in emerging markets are more vulnerable to capital mobility than developed economies.

4.3.3.3 Comparing with Existing Empirical studies

The results of this chapter are compared with other studies regarding the performance of individual explanatory variables. As shown in the highlighted parts of Table 4.8, it is found that the coefficient signs of macroeconomic variables in predicting crisis and post-crisis periods in this chapter tend to be in harmony with those predicting the pre-crisis and crisis periods in existing studies. Thus, while the results of existing empirical studies imply that banking crises are preceded by recession, depreciation, undervaluation and capital outflow, the current empirical results imply that banking crises are succeeded by recession, depreciation, undervaluation, capital outflow. In contrast, the chapter finds that the economy still "thrives" in the "pre-crisis" period in terms of increasing GDP growth.

The inconsistency in results is very likely due to imprecise identification of crises in previous studies. In the majority of existing studies, as reckoned by Hardy (1998), a crisis is defined as starting when intervention became necessary, but often the banks' asset deterioration is widely known for some time before then, which is reflected in the stock prices. The lateness in crisis identification shifts the "boom and bust" pattern forward, either causing the illusionary "recession" before crises or resulting in insignificance of explanatory variables. Moreover, "pre-crisis bias" is rarely addressed in existing studies, as explained earlier, and also contributes to the inconsistency in results.

4.4 Conclusion

Existing empirical studies have generally attributed macroeconomic roots to banking sector fragility. They conclude that banking crises/distresses are preceded by deteriorating macroeconomic conditions and therefore can be predicted by macroeconomic indicators such as a dramatic fall in the real GDP growth rate, a fall in the exchange rate and capital outflow. Their results were applied pervasively by central banks to establish an early warning system of future distress.

However, in an episode of banking system distress, macroeconomic variables not only show downward movement, but also display upward movement. The boom and bust pattern is displayed both in the lead-up to a crisis and after the crisis begins unfolding. Therefore, the results of the existing studies are crucially dependant on correct crisis identification of historical crises. However, the existing studies share a common problem in the dependent variable of their model. They all rely on indirect events or indices such as bank closures, government intervention and money market pressure, to identify historical bank crises/distress, while they opine that banking sector difficulties have often been widely recognised for some time before then. The problems originate from a deterioration of bank asset quality, the data of which are often not available during the sample period of existing studies. Thus, the results of the existing studies can be subject to important caveats.

Using direct stock market data to identify crises, this chapter performs an empirical study verifying the macroeconomic determinants of banking crises proposed by earlier studies. The results corroborate the "boom and bust" pattern around crises. In particular, it is found that the economy still thrives in the "pre-crisis" period in terms of increasing GDP growth. This is in contrast with earlier empirical studies, which conclude that the downward movements precede the onset of crises. However, it is discovered that the economic downturn in terms of a fall in GDP growth is generally associated with the post-crisis period. As the "bust" parts appear to be shifted afterwards in this chapter, it is concluded that the inconsistency of results is very likely due to the imprecise crisis identification of earlier studies. The existing studies often identify crises too late on the basis of indirect symptoms.

Table 4.1: Key results of empirical studies of determinants of banking crises

Empirical studies	Indicator studies	Binomial Model				Multinomial Model	
	KR 1999	**ER 1998**	**DD 1998**	**HH 2003**	**HM 1999**	**HP 1999**	
Macroeconomic Environment						**Pre-crisis**	**Crisis**
Real GDP growth	<0.14	-* (contemp.)	-*** (contemp.)	-*** (lagged 1q)	-*** (contemp.)	Insig. (contemp.)	-*** (contemp.)
Inflation			+** (contemp.)	+*** (lagged 1 q)	-Insig. (contemp.)	-* (contemp.) +*** (lagged 2y)	-*** (contemp.)
Domestic real interest	>0.80		+*** (contemp.)	-**/Insig. (lagged 1	Insig. (contemp.)	+ (lagged 1y)	+ (contemp.)
External factors							
Depreciation	>0.10		Insig. (contemp.)	+*/Insig. (lagged 1	Insig. (contemp.)	+*/Insig. (contemp.)	-** (contemp.)
Overvaluation		+* (contemp.)		-* (lagged 1			
M2/Reserves	>0.9		+** (contemp.)				
Short-term foreign debt		Insig. (contemp.)				+*/Insig (contemp.)	-Insig (contemp.)
Credit boom and bust							
M2 Multiplier	>0.9		-* (contemp.)				
Credit growth	>0.95	Insig. (contemp.)	+** (lagged 2y)	-Insig. (contemp.) (lagged 2q)	-*/Insig. (contemp.)	-Insig (contemp.) (lagged 1y)	-Insig. (contemp.)
Institutional factors							
GDP /capita			-*	Insig.			
Estimation method		Probit	Logit	Logit	Probit	Logit	

Note: one, two and three asterisks indicate significant levels of 10, 5, and 1 percent, respectively. Insig., contemp. and q represent respectively insignificance, contemporaneous, and quarter.

Table 4.2: Comparison of banking crisis dates identified between 1990 and 2005

	Event Study						MMP	IBS
	Caprio & Klingebiel (1996)	**Demirgüc-Kunt & Detragiache (1998)**	**Kaminsky & Reinhart (1999) (Beginning)-(Peak)**	**Bordo & Schwarz (2000)**	**Glick & Hutchison (2001)**	**World bank database (2003)**	**Calculated based on Hagen & Ho (2007)**	**This Chapter**
Frequency	*Annual*	*Annual*	*Monthly*	*Annual*	*Annual*	*Annual*	*Quarterly*	*Quarterly*
Australia	n/a	n/a	n/a	n/a	n/a	1991-1992	96Q3 01Q4	91Q1 99Q3
Denmark	n/a	n/a	n/a	n/a	n/a	1990-1992	93Q1 00Q3 04Q1	93Q1 99Q1 02Q1
Korea	n/a	n/a	n/a	n/a	n/a	1997-2002	91Q2 97Q4	97Q1
Malaysia	n/a	n/a	n/a	n/a	n/a	1997-2001	91Q3 93Q3 95Q1 97Q2	94Q3 98Q1
Mexico	1995	1994	Oct 1992-Mar 1996	1994	1995-97	1994-2000	94Q4 99Q4	93Q1 99Q1
The Philippines	n/a	n/a	Jul 1997-Ongoing	No	1997	1998-	90Q1 92Q1 97Q3	91Q2 94Q1 98Q1 02Q1
Thailand	n/a	No	May 1996-Ongoing	1997	1997	1997-2002	97Q3	97Q2 00Q1
The UK	No	No	n/a	n/a	No	1990s	95Q4	91Q1 94Q3 99Q1
The US	1984-91	1981-92	n/a	n/a	n/a	1988-1991	01Q4	91Q1 99Q1 02Q1

Table 4.3: Comparison of existing studies and this chapter in dealing with pre-crisis and post crisis bias

Logit model	Literature	Pre-crisis obs.	Post-crisis obs.	Summary
Binomial	ER 1998 & HM 1999	3 years eliminated	3 years eliminated	Eliminating all obs. around crises
	DD 1998	Unconsidered/treated as tranquil	All obs. eliminated	Ignoring "pre-crisis" bias
		Unconsidered/treated as tranquil	Identify the end of crises	
	HH 2002	Unconsidered/treated as tranquil	8/12/16 quarters after crisis eliminated	
Multinomial	HP 1999	2 year	Unconsidered/treated as tranquil	Ignoring "post-crisis" bias
	This chapter	8 quarters	8 quarter obs. eliminated	Considering both "pre-crisis" and "post-crisis" bias
			Categorise 8 quarters after crisis	

Table 4.4: Description of explanatory variables and their relative value compared to a non-crisis period.

Explanatory variables	Definition & Source
1. Macroeconomic indicators	
GROWTH	Gross Domestic Production (IFS 99BVPZF) divided by GDP deflator (IFS line 99BIPZF) in annual percentage changes.
INFLATION	CPI (IFS line 64...ZF) in annual percentage changes.
PRMMR	Money market rate (IFS line 60B..ZF) minus inflation rate in percentage change over the previous year.
2. External competitiveness	
PREER	Real Effective Exchange Rate (IFS line ...REUZF) in percentage, change over past two years
OVREER	Over-valuation of the real effective exchange rate or REER (IFS line ...REUZF) from trend (use HP filter). For Thailand that REER is not available, real exchange rate per US dollars (IFS line ae) adjusted for CPI (IFS line 64...ZF) is used.
3. Capital outflow	
M2RES	M2/Reserves. M2 (IFS lines 34 plus 35) converted into dollars (using IFS line ae) divided by IFS line lL.d
PFORDEBT	Foreign liabilities of domestic commercial banks (IFS line 26C..ZF) in percentage change over the previous years.
4. Over-lending cycle	
CREDITGRO	Credit growth rate. The ratio of Claims on Private Sector (IFS line 22D..ZF) deflated by CPI (IFS line) to real GDP. In annual percentage changes
5. Institutional & regional factor	
GDP/CAP	Real GDP per capita (Population IFS line 99Z)
DEVDFODEBT_	PFORDEBT multiplied by regional dummy for emerging markets.

Table 4.5: Sample Mean of Explanatory Variables

	Non-crisis	Pre-crisis	Crisis	Post-crisis
DFODEBT_	16.5362	26.5234	14.8841	5.3861
	(24.3026)	(32.5035)	(24.3066)	(20.0882)
GDPCAP_	0.0366	0.0462	0.0424	0.0423
	(0.0451)	(0.0572)	(0.0549)	(0.0563)
GROWTH_	0.2997	-1.7701	-4.0607	-2.1859
	(3.943)	(5.7099)	(8.6112)	(6.7508)
INFL_	3.8808	5.9564	6.9311	5.3931
	(3.5986)	(5.6811)	(8.9298)	(7.2655)
M2MULTI_	1029.1136	107.1294	83.7662	124.6779
	(2502.282)	(445.4181)	(349.6669)	(468.702)
M2RES_	2.6447	2.7582	2.7671	2.3304
	(5.0806)	(4.7839)	(5.0832)	(4.366)
OVREER_	-0.3335	1.3524	-1.1397	-1.4429
	(4.5086)	(7.0682)	(8.1409)	(6.6429)
PCREDGRO_	8.0438	18.6996	8.8656	3.1755
	(12.4973)	(42.3993)	(13.6389)	(11.2916)
PREER_	1.1008	1.8221	-2.9875	0.7712
	(5.8408)	(11.7985)	(10.9427)	(13.4184)
RMMR_	2.6984	4.9736	4.0352	3.2273
	(3.0156)	(6.6251)	(4.7438)	(3.2663)
NO. period	231	177	24	144
T-critical		1.97	2.07	1.98

Note: standard errors are given in parentheses.

Table 4.6: Multinomial regressions excluding post-crisis observations.

	y_1=1	y_1=2	y_1=1	y_1=2
C	-1.808007*** (0.235931)	-2.758652*** (0.484413)	-2.700013*** (0.347408)	-3.145884*** (0.841050)
GROWTH_	0.041581 (0.044849)	-0.211915** (0.096044)	0.161506*** (0.057432)	-0.164183 (0.111191)
INFL_	0.147985*** (0.043602)	-0.008336 (0.104459)	0.328617*** (0.067050)	0.076967 (0.143373)
RMMR_	0.217689*** (0.034057)	0.161508*** (0.059989)	0.258262*** (0.036536)	0.178993** (0.074375)
PREER_	-0.021043 (0.017016)	-0.066677 (0.049250)	-0.028724 (0.018086)	-0.075028 (0.056235)
OVREER_	0.074386*** (0.028607)	0.058258 (0.062823)	0.103676*** (0.029984)	0.074822 (0.069220)
M2RES_	-0.029482 (0.021501)	0.003553 (0.046875)	-0.051911** (0.024292)	0.004036 (0.047959)
DFODEBT_	0.004790 (0.004175)	-0.014473 (0.015353)	0.039287*** (0.013164)	-0.001985 (0.023236)
PCREDGRO_	0.007704 (0.006223)	-0.020449 (0.024527)	0.008495 (0.007097)	-0.020286 (0.029682)
CORR_			0.175267 (0.215913)	0.146956 (0.558334)
GDPCAP_			1.979930 (2.200976)	1.682726 (5.139886)
DEVDFODEBT_			-0.034899*** (0.013069)	-0.012466 (0.042969)
% Total correct	72.75	95.18	73.61	95.24
% Y=1 or 2 correct	45.76	4.17	51.41	4.17
% non-crisis correct	88.67	100.00	85.63	99.79
Included Obs	504		504	
Number of crises	24		24	
Log likelihood	-341.4532		-326.3305	
Akaike info criterion	1.434338		1.406074	

Note: one, two and three asterisks indicate significant levels of 10, 5, and 1 percent, respectively.

Table 4.7: Multinomial regressions include post-crisis observations

	y_2=1	y_2=2	y_2=3	y_2=1	y_2=2	y_2=3
C	-2.045573*** (0.235855)	-3.043043*** (0.451259)	-0.544027*** (0.173050)	-2.809442*** (0.331816)	-3.148192*** (0.865785)	-0.623926** (0.23842)
GROWTH_	0.072697 (0.043842)	-0.116289 (0.085713)	-0.147788*** (0.022551)	0.175393*** (0.055117)	-0.111000 (0.103863)	-0.144131* (0.022762)
INFL_	0.102177** (0.043322)	-0.044505 (0.081004)	-0.080615 (0.019724)	0.243033*** (0.061488)	-0.019972 (0.128364)	-0.07053*** (0.022794)
RMMR_	0.139666*** (0.032139)	0.005829** (0.064351)	0.015938** (0.034790)	0.179364*** (0.033674)	0.015587** (0.080300)	0.027329*** (0.035190)
PREER_	-0.012269 (0.014626)	-0.046134 (0.045759)	0.016577 (0.012060)	-0.015366 (0.014216)	-0.050260 (0.061680)	0.016499 (0.010854)
OVREER_	0.070755** (0.026283)	0.050153 (0.062168)	-0.063158 (0.022325)	0.096028*** (0.027042)	0.057507 (0.071953)	-0.063119 (0.020326)
M2RES_	-0.021019 (0.021179)	-0.012150 (0.046238)	-0.005852 (0.025298)	-0.038015** (0.023662)	0.014648 (0.048198)	-0.008615 (0.025425)
DFODEBT_	0.009852 (0.004359)	-0.007040 (0.015553)	-0.018035*** (0.005187)	0.037090*** (0.012397)	-0.011421 (0.022866)	-0.009985 (0.010780)
PCREDGRO_	0.014688 (0.008652)	-0.006749 (0.023072)	-0.047211*** (0.009491)	0.017058 (0.009738)	-0.006301 (0.030514)	-0.04779*** (0.010074)
GDPCAP_				2.004695 (2.167019)	1.127717 (4.949160)	-0.492290 (2.095535)
DEVDFODEBT_				-0.029266*** (0.012171)	0.004902 (0.046237)	-0.011796** (0.013578)
DEVM2RES_				-0.286811*** (0.109494)	-0.187006 (0.212924)	-0.098249 (0.101499)
% Total correct	75.00	96.30	80.68	75.93	96.30	79.78
% Y=1, 2 or 3 correct	23.16	0.00	24.31	29.94	0.00	18.75
% non-crisis correct	94.48	100.00	97.69	93.21	100.00	97.22
Included Obs		648			648	
Number of crises		24			24	
Log likelihood		-591.1529			-570.1085	
Akaike info criterion		2.156781			2.125377	

Note: one, two and three asterisks indicate significant levels of 10, 5, and 1 percent, respectively.

Table 4.8: Comparison of results with existing studies

Macroeconomic Variables	Binomial Model				Multinomial Model		Multinomial Model		
					HP 1999		**This chapter**		
	ER 1998	**DD 1998**	**HH 2002**	**HM 1999**	**Pre-crisis**	**Crisis**	**Pre-crisis**	**Crisis**	**Post-crisis**
Real GDP growth	-*	-*** (contemp.)	-*** (lagged 1q)	-*** (contemp.)	Insig.	-***	+**	-Insig	-**
Inflation		+** (contemp.)	+*** (lagged 1 q)	-Insig.	-* (contemp.)	-***	+**	-Insig	-**
Domestic real interest rate		+*** (contemp.)	-**/Insig. (lagged 1 q)	Insig.			+**	+Insig	+Insig
Depreciation		Insig.	+*/Insig.	Insig.	+*/Insig.	-**	-Insig	-Insig	+Insig
Overvaluation	+*		-* (lagged 1 q)				+***	+Insig	-***
M2/Reserves		+** (contemp.)					-Insig	+Insig	-Insig
Short-term foreign debt	Insig.				+*/Insig	-Insig	+***	-Insig	-*
M2 Multiplier		-* (contemp.)							
Credit growth	Insig.	+** (lagged 2y)	Insig. (lagged 2q)	-*/Insig.	-Insig (contemp.) (lagged 1y)	-**/Insig.	+**	-Insig	-***
GDP /capita		-*	Insig.				+Insig	+Insig	+Insig

Note: one, two and three asterisks indicate significant levels of 10, 5, and 1 percent, respectively.

Appendix 4.1

Crisis Identification by Markov switching model

The Markov switching model is used here to find a crisis threshold that maximises the log likelihood function of the Bank Stock Index (IBS). The model starts with assuming different means (β_{S_t} as below) and variances ($\sigma^2_{S_t}$) in two regimes (S_t), i.e. crisis (S_t =1) and a tranquil period (S_t =0). It is expected that crisis periods may have a lower mean and a larger variance than the tranquil periods. The index is formulated below:

$$y_t = IBS_t = \beta_{S_t} + e_{S_t}, \quad e_{S_t} \sim N(0, \sigma^2_{S_t}) \tag{4.7}$$

$$\beta_{S_t} = \beta_0(1 - S_t) + \beta_1 S_t \tag{4.8}$$

$$\sigma^2_{S_t} = \sigma^2_0(1 - S_t) + \sigma^2_1 S_t \tag{4.9}$$

$$S_t = 0, or\, 1 \tag{4.10}$$

Therefore, under regime 1, parameters are given by β_1 and σ^2_1, and under regime 0, parameters are given by β_0 and σ^2_0. In this case, the log likelihood function is given by:

$$\ln L = f(y_t \mid \psi_{t-1}) = \sum_{t=1}^{T} \ln(f(y_t \mid S_t) \tag{4.11}$$

where

$$
\begin{aligned}
f(y_t \mid S_t) &= \frac{1}{\sqrt{2\pi\sigma_{S_t}^2}} \exp\left(-\frac{\{y_t - \beta_{s_t}\}^2}{2\sigma_{S_t}^2}\right) \\
&= \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left(-\frac{\{y_t - \beta_{s_0}\}^2}{2\sigma_0^2}\right) \times \Pr[S_t = 0 \mid \psi_{t-1}] \\
&+ \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left(-\frac{\{y_t - \beta_{s_1}\}^2}{2\sigma_1^2}\right) \times \Pr[S_t = 0 \mid \psi_{t-1}]
\end{aligned} \tag{4.12}
$$

where ψ_{t-1} refers to information up to time t-1. The log likelihood function then is given by:

$$
\ln L = \sum_{t=1}^{T} \ln\{\sum_{S_t=0}^{1} f(y_t \mid S_t, \psi_{t-1}) f(S_t \mid \psi_{t-1})\} \tag{4.13}
$$

However, to maximise the equation (4.13) with respect to $\beta_0, \beta_1, \sigma_0^2, \sigma_1^2$, the weighting factors, $\Pr[S_t = 0 \mid \psi_{t-1}]$ and $\Pr[S_t = 1 \mid \psi_{t-1}]$ need to be calculated. Without a priori assumptions about the stochastic behaviour of the S_t variable, this will not be possible. The simplest first-order Markov switching model assumes that S_t is dependent upon S_{t-1}. The paper employs the iteration procedure of Kim and Nelson (1999) to deal with the unobserved S_t. Furthermore, it modifies the Eviews program by Ho (2004) to suit the situation for this paper. Ho (2004) uses a grid search to start the estimation. The final estimate is the one with highest likelihood value. The banking crisis dates identified are listed in the following table. The results verify the conclusion in Ho (2004). The method invents too many crises for some countries, for example, the UK has crises in almost every period of the sample. Moreover, for countries that have had a few crises, the results fail to include the most well-known crisis episodes in the data, for example, the 1997-1998 crisis in Korea, the Philippines and Thailand.

Table 4.9: Banking crisis dates identified by simple Markov-switching model.

Country	Identified Banking Crises			
Australia	1991Q3	1992Q1	1992Q3	1993Q2
	1993Q4	1994Q1	1994Q4	1995Q2
	1995Q4	1996Q4	1997Q1	1997Q3
	1997Q4	1998Q3	1999Q1	1999Q2
	2000Q1	2000Q3	2001Q1	2001Q3
	2002Q1	2002Q3	2003Q3	2004Q2
	2005Q1	2005Q2	2005Q4	2006Q2
	2007Q3			
Denmark	1990Q2	1990Q4	1991Q2	1991Q4
	1992Q2	1992Q4	1993Q2	1993Q4
	1994Q2	1994Q4	1995Q2	1995Q4
	1996Q2	1996Q4	1997Q2	1997Q4
	1998Q2	1998Q4	1999Q2	1999Q4
	2000Q2	2000Q4	2001Q2	2001Q4
	2002Q2	2002Q4	2003Q2	2003Q4
	2004Q2	2004Q4	2005Q2	2005Q4
	2006Q2	2006Q4	2007Q2	2007Q4
Korea	1999Q1			
Malaysia	1993Q4	1994Q1	1994Q2	1994Q3
	1998Q1	1998Q2	1998Q3	1998Q4
	1999Q1	1999Q2	1999Q3	1999Q4
	2000Q1	2000Q2	2000Q3	2000Q4
Mexico	1990Q2	1990Q3	1990Q4	1991Q1
	1991Q2	1991Q3	1991Q4	1992Q1
	1992Q2	1992Q3	1992Q4	1993Q1
	1993Q2	1994Q2	1995Q1	1995Q2
	1995Q3	1999Q1	1999Q2	1999Q3
	1999Q4	2000Q1	2000Q2	2001Q4
The Philippines	1994Q2			
Thailand	1999Q2			
The UK	1990Q2	1990Q3	1990Q4	1991Q1
	1991Q2	1991Q3	1991Q4	1992Q1
	1992Q2	1992Q3	1992Q4	1993Q1
	1993Q2	1993Q3	1993Q4	1994Q1
	1994Q2	1994Q3	1994Q4	1995Q1
	1995Q3	1995Q4	1996Q1	1996Q2
	1996Q3	1996Q4	1997Q1	1997Q2
	1997Q3	1997Q4	1998Q1	1998Q2
	1998Q3	1998Q4	1999Q1	1999Q2
	1999Q3	1999Q4	2000Q1	2000Q2
	2000Q3	2000Q4	2001Q1	2001Q2
	2001Q3	2001Q4	2002Q1	2002Q2
	2002Q3	2002Q4	2003Q1	2003Q2
	2003Q3	2003Q4	2004Q1	2004Q2

	2004Q3 2005Q3 2006Q3 2007Q3	2004Q4 2005Q4 2006Q4 2007Q4	2005Q1 2006Q1 2007Q1	2005Q2 2006Q2 2007Q2
The US	1991Q1	1999Q1		

CHAPTER FIVE

CONCLUSION

The previous three chapters investigate empirically various topics regarding the systemic risk of the banking sector and conclude that pre-2007 risk assessment models underestimate the systemic risk of the banking sector and justify an overhaul in terms of: assessing the contagion impact of the interbank market; testing market discipline of interbank lending and verifying macroeconomic indicators of banking crises.

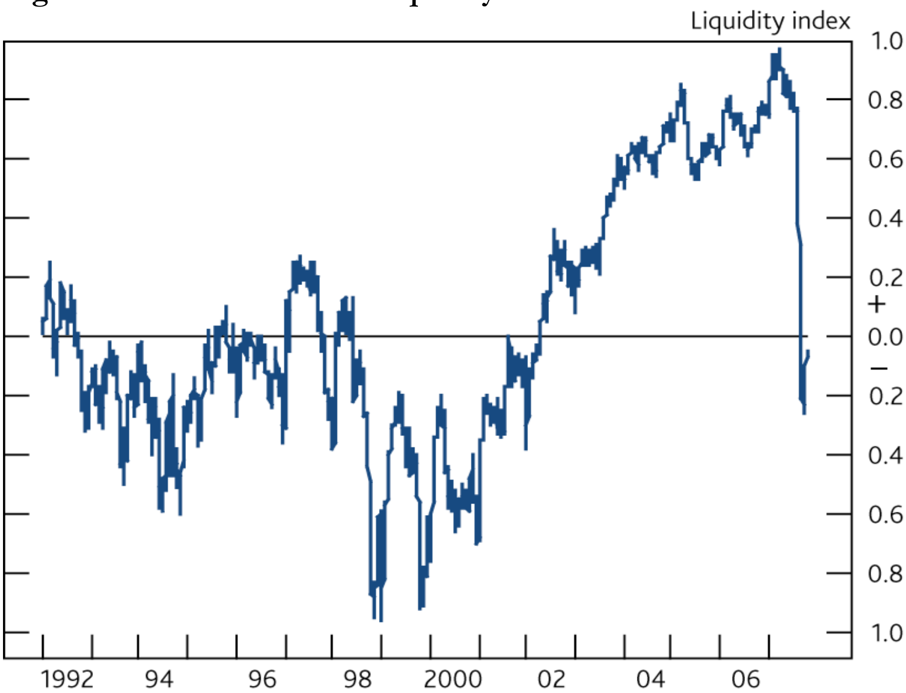
Specifically, Chapter 2 indicates that wide-scale contagion is more likely than the previous studies suggest. The results agrees to the argument put forward by Allen and Gale (2000) and Freixas, Parigi and Rochet (2000) who regard the interbank exposure or the credit linkage between banks as a source of contagion. Default of any banks in the netting system is likely to trigger a chain reaction of defaults, resembling the fall of dominoes. And the risk of interbank contagion is sensitive to the pattern of linkages/market structure. Before the current global crisis occurs, central banks in various countries especially in Europe (Switzerland, Germany, Austria, Denmark, UK, Belgium) applies a network approach to track the reverberation of a credit event or liquidity squeeze throughout the banking system via direct linkages in the interbank market. All of them find only limited or low contagion impact. However, the author find that their results are crucially subject to various assumptions such as the evolution of market structures, the choice of data, default rate, and other factors that could lead to bias to the result in one or mixed direction. Most significantly, the author compares the simulation using consolidated data to those using unconsolidated data in other studies. This means that the thesis takes account of the fact that the subsidiaries and their headquarters normally stand or fall together, which is generally ignored by previous literatures. As the banking industry becomes increasingly integrated and concentrated---large banks usually owning a significant number of subsidiaries, using unconsolidated data simulation would seriously mislead central banks' view in assessing the systemic implications of financial linkages. The results of the thesis show that the contagion impact in the UK interbank market using consolidated data is much severe, i.e. 89.48% of the total balance sheet assets are affected in the worst scenario at a LGD rate of 100%, compared with 25.25% in Wells (2004) who uses unconsolidated data. The inconsistency is analyzed in a pseudo-four-bank illustration. It shows that the average interbank exposure relative to tier-I capital is larger in the system of consolidated exposure than that of unconsolidated exposure. The author assesses two years before 2004 and finds a similar wide-scale contagion between 2004 and 2003, accounting for 90% of total banking sector assets, but a limited impact in 2002, accounting for only 12.57%. This is attributed to higher interbank exposure relative to Tier-1 capital in 2003 and 2004 compared to 2002. Given more data available, the future work would make more years comparable.

As bilateral exposure data of individual banks are not released to the public, the thesis has to follow the previous literature which applies Entropy Maximization approach. Although the approach is sensible in that it assumes that the bilateral exposure is in proportion and subject to the size of the creditor and borrowing bank's total interbank exposure to the market, it has the limitation in assuming that banks seek to maximize the dispersion of their interbank activity, i.e. banks spread their lending as evenly as possible among all the other banks. Relationship banking is ruled out in which banks normally have a few fixed clients to transact with. Although this thesis tries to overcome this limitation by varying the weights in the "matrix" that allows testing alternative market structures/relationship banking, it is optimal to perform the simulation based on actual data. Mistrulli (2005) has compared results using EM and actual data and concludes that EM approach that resembles complete market results tend to under-estimate the extent of contagion as many countries are featured by money centre structure. However, he also indicates that under certain circumstances, depending on the structure of the interbank linkages, the recovery rates of interbank exposures and banks' capitalisation the maximum entropy approach overestimate the scope for contagion.

Moreover, future studies would compare the results using EM (network approach) with other three approaches summarized in the IMF Global Financial Stability Report (2009), i.e. co-risk model, distress dependence matrix, and the default intensity model. The network approach distinguish from others in that it offers important insights on which institutions are critical for financial stability and how the structure of the interbank market affects the scope for contagion; the co-risk model exploits market data to assess systemic linkages among financial institutions under extreme events; the distress dependence matrix examines pairs of institutions' probabilities of distress, taking into account a set other institutions; and the default intensity model measures the probability of failures of a large fraction of financial institutions due to both direct and indirect systemic linkages. As indicates in the Report (2009) and Upper (2003), although each approach by itself has considerable limitations and has different research focus, together they represent a set of valuable surveillance tools and can form the basis for policies to address the too-connected-to-fail problem in various settings such as stress testing, allocating scarce supervisory resources, analysing the costs and benefits of regulating.

Together with Chapter 2, Chapter 3 corroborates Freixas, Parigi and Rochet (2000)'s argument that interbank do not always co-operate properly, especially during crises, when all banks find it optimal to withdraw bank loans for fear that other banks will not be able to honour their obligations if their depositors withdraw all their wealth. As Figure 5.1 shows, the UK financial market comes to a deadlock in providing liquidity not only in the current crisis close to 2007, but also in late 90s when US Long-Term Capital Management (LTCM) and Russian Rupee collapse and the US dot-com bubbles start to burst. Even during "peace" time between 2000 and 2006, the results of Chapter 3 indicate that the interbank market does not discipline. With increasing liquidity during this period, the riskiness of banks virtually mounts as well.

Figure 5.1 Financial market liquidity in UK 1992-2007



Sources: Bank of England (April 2007 *Report,* Box 2: Financial market liquidity, page 18.), Bloomberg, Chicago Board Options Exchange, Debt Management Office, London Stock Exchange, Merrill Lynch, Thompson DataStream and Bank calculations. The liquidity index shows the number of standard deviations from the mean. It is a simple unweighted average of nine liquidity measures, normalised on the period 1999-2004.

This is against the argument proposed by Rochet and Tirole (1996) who argue that by generating incentives for peer monitoring, the existence of interbank exposure may facilitate prudent market behaviour and reduce the risk of bank failure and systemic distress.

Chapter 3 challenges the results of many pre-2007 models which corroborate Rochet and Tirole (1996) and conclude that the existence of interbank exposure may facilitate prudent market behaviour and reduce the risk of bank failure and systemic distress. It finds that there are crucial limitations of these studies in defining how market disciplines. Furfine et al on US market check lenders' risk sensitivity but do not demonstrate that monitoring incentives can effectively control the risk of the borrowing banks. Dinger and Hagen on European market confirm negative correlation between the risk and their interbank borrowing position, without first confirming the monitoring incentives of the lenders. The correlation could be spurious and the reduction of bank risk could well be due to factors other than interbank borrowing.

The author insists a two-step procedure to test the interbank market discipline. The 1st step tests risks sensitivity or the monitoring incentive of the interbank lending banks; the 2nd step tests the effectiveness of risk control under monitoring. The approach applied on UK interbank market find little evidence of market discipline in UK. Specifically, the results show weak risk sensitivity and no effectiveness of risk control. The chapter finds that the weak lender accountability is due to two factors. First, many of the large banks are net interbank borrowers and therefore the disciplining incentives could be hampered by 'too-big-to-fail' consideration; second, more than 80% of the transactions are less than three months, so the lenders can fly easily and escape their monitoring obligations. In a theoretical model to explain the ineffectiveness of risk control, the author justifies the two-step approach to test market discipline. The model demonstrates that even with peer monitoring, banks financed by interbank fund could choose a riskier asset portfolio to maximize their net expected return. This happens when: the "bad" assets are much riskier than the "good" assets and the probability that both "bad" assets and "good" assets repay is very small.

For future work, the author is very keen to look at the short-term interbank market performance in UK as well as long-term effect, provided with longer sample period and shorter data frequency. Co-integration test and error correction model can be applied to verify the relationship between the riskiness of a bank and its net interbank lending position. However, the author foresees the similar difficulties of applying to panel data, because co-integration test is devised initially to test two non-stationary time series variables and may have the same limitation as Granger test. As explained in Chapter 3, the existing econometric panel variants of those tests provide no indication as to the number or the identity of the particular panel members for which the null hypothesis is rejected. Moreover, it is also possible in the future studies to investigate risk pricing in the UK interbank market, if public data regarding the individual interbank rate data are available.

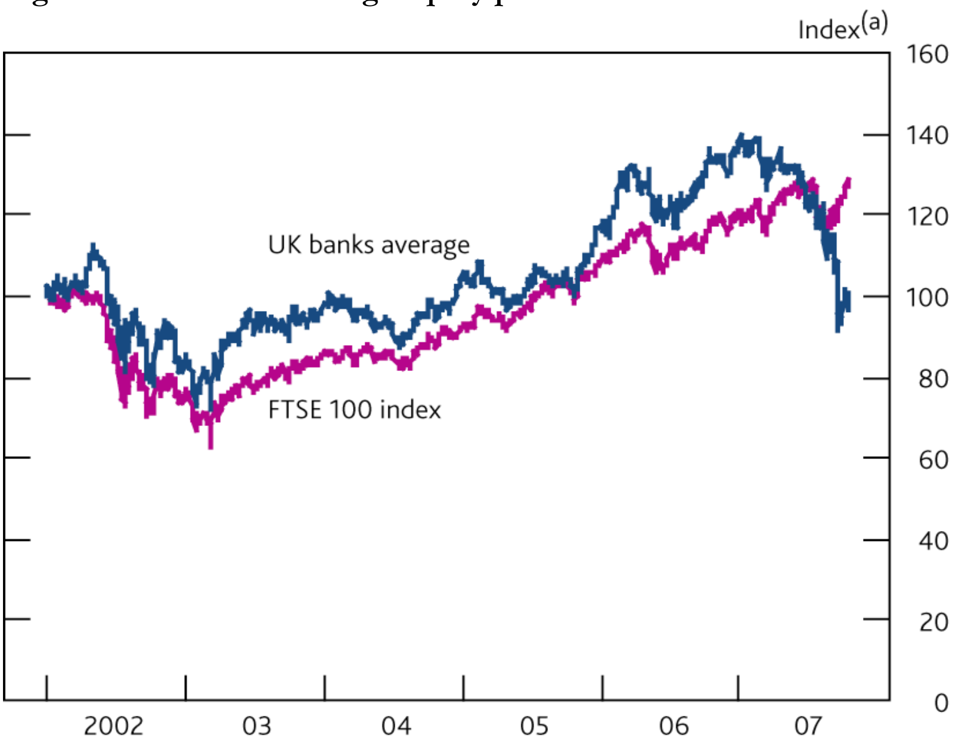
In addition, although Chapter 3 measures the riskiness of a bank from different sources, i.e. market level and supervisory level, there is certainly avenue to look at new risk measures. For example, the World Bank has updated the new z-score measurement for banks in 2009 report by Demirgüç-Kunt and Huizinga. Furthermore, when assessing banks' riskiness based on their capital adequacy ratio, future studies have to take account and adjust for the difference between Basel I and Basel II. Nevertheless, this is not a significant issue to this thesis, as UK banks do not start to formally apply Basel II until 2007 while the sample period of Chapter 3 is mostly governed by Basel I except for the year of 2007. Last, more thought will be given in the future study to extend years to include current credit crunch and test if they constitute a structural difference. Crisis years can be incorporated as dummies to see the different performance.

Furthermore, reputation and counterparty risk have featured greatly in discussions of the breakdown of interbank lending and this suggests that the effectiveness of peer monitoring might be impaired as a result of 'opacity' (asymmetric information). This also conflicts with the argument of Rochet and Tirole (1996) and Calomiris (1998) who assume banks possess the technology to differentiate the risks of other banks. Future work will be developed on Anderson and Mullineux (2009) who suggest that in order to reduce perceived counterparty risk, bank regulators must cut through the opacity of banks' balance sheets lest interbank lending which, in ordinary times, channels loanable funds to the most eager borrowers dries up.

Chapter 4 fits well with the current policy debate regarding "wait and clean up versus preventive action". In the context of current crisis, it seems that Greenspan and Bernanke are wrong arguing "market efficient" and that it is better to clean up after the mess, rather than spoil the party. Indeed the current crisis tends to revive the reputation of Minsky, who together with William McChesney Martin argued that central banks should take away the 'punch bowl' before the party gets started, tend to be right. Perhaps most significantly, Chapter 4 indicates that we do not always need a deterioration of economic conditions to cause a crisis, indeed the 'Great Moderation' in the US and the 'NICE' decade in the UK may have caused it (by encouraging over borrowing and over lending and the under pricing of risks i.e. a credit boom). And the results are also consistent with Honohan (1997) who is sceptical that banking systems collapse because of macroeconomic shocks, as some of them have survived very severe macroeconomic shock. Chain breaks as the result of the homogeneous weakness of all links.

However, the controversy over whether macroeconomic variables are worth watching closely in predicting future banking crises originates the fact that some of these variables typically display a distinctive boom and bust pattern, both in the lead-up to an episode of banking system distress and while the episode is unfolding. In contrast to almost all existing studies, the chapter finds that economy still "thrives" in the "pre-crisis" in terms of increasing GDP growth while the recession in terms of a fall in GDP growth is generally associated with the post-crisis period. And the thesis find the inconsistency with the earlier empirical studies is very likely due to crisis identification. Earlier studies that use "event studies" could identify crises too late on the basis of indirect symptoms, such as bank closures, forced merger and take-overs and large-scale government bailout. They admit themselves that banking sector difficulties exist for some time before that point. Base on those "late detection", the macroeconomic variables display their "down-turn" movement in the pre-crisis period. Stock market indices are used to replace the old methods because it is commonly agreed in the existing literature that banking crises occur from the protracted deterioration of banks' asset quality (which consequently causes banks to halt to trust each other and drive up the interest rate premium in various markets). The collapse in the banking sector stock in 2007 is shown in Figure 5.2.

Figure 5.2 UK banks average equity prices 1992-2007



Sources: Bloomberg and Bank Calculations

(a) Rebased to 100 on 2 January 2002

However, the stock market data was largely unavailable for the sample period and targeting countries for previous studies. Data of non-performing loans is not a good alternative because they normally released on an annual basis and figures may be less informative due to banks' incentive to hide their problems as long as possible. Banking crises are defined in this thesis as when the stock market indices of banking sector are lower than its historical 0.5 percentile independent of the effect of the general market movement. The threshold is somewhat arbitrary. However, the thesis finds no better way to resolve it and opens an avenue for future studies. Moreover, future work will extend Chapter 4 to test if the macroeconomic disturbances to be endogenous, an argument of the current "Minsky moment" which emphasizes those crises, to some extent, are caused by the banking systems themselves.

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